The Dissertation Committee for Young Sin Yoo Certifies that this is the approved version of the following dissertation:

The Potential Impacts of Global Climate Change on U.S. Agriculture

Committee:

Don Fullerton, Supervisor

Stephen P. Magee

Stephen G. Donald

Peter J. Wilcoxen

Roberton C. Williams

The Potential Impacts of Global Climate Change on U.S. Agriculture

by

Young Sin Yoo, B.A., B.A., M.S.

Dissertation

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

Doctor of Philosophy

The University of Texas at Austin

August, 2002

Dedication

To my family and colleagues

The Potential Impacts of

Global Climate Change on U.S. Agriculture

Publication No._____________

Young Sin Yoo, Ph.D.

The University of Texas at Austin, 2002

Supervisor: Don Fullerton

My dissertation estimates the economic effects of anthropogenic-induced climate change on U.S. agriculture. The dissertation postulates from the outset that farmers optimally adapt to varying environmental conditions. Thus, land prices can be used to measure the highest value use of the land. Using this assumption, this paper attempts to extend previous research on this subject in three ways. The first goal is to estimate the distributional effects of climate change on U.S. agriculture. Even though many researchers agree that the U.S. agricultural sector is likely to experience a shift of regional comparative advantage in response to changing climate, few studies actually quantify the distributional effects of global warming on U.S. agriculture. The main focus of my dissertation, therefore, is not only to estimate the aggregate impacts of climate

change on U.S. agriculture, but also to examine how each region of the United Stated may be affected by changing climate. Second, most researchers believe that the pattern of climate change will be uneven across the North American continent, inducing diverse effects across different regions. Instead of assuming uniform changes in climate variables (e.g., temperature and precipitation), therefore, this research takes into account the possibility of variations in climate change across the 48 contiguous United States. Third, the dissertation accounts for the temporal aspects of anthropogenic-induced climate change. Most impact studies in the past were based on arbitrary climate change scenarios or the equilibrium-doubled CO_2 General Circulation Model (GCM) scenarios in projecting the effects of global warming on US agriculture. In order to capture the time-dependent responses of the climate system and their impacts on US agriculture, however, this project uses transient climate change scenarios that allow an examination of the time-path of climate change in each U.S. county. Applying the Ricardian approach proposed by Mendelsohn et al. (1994) in estimating the potential impacts of global warming on U.S. agriculture, my dissertation finds that the U.S. agricultural sector is resilient enough to cope with greenhouse gases-induced climate change. Some regional impacts may be disruptive, however, especially if future climate changes as projected by the Canadian model (CGCM1-TR), in which the Southern Plains (Texas, Okalahoma) is the most vulnerable region.

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Chapter 1: Introduction

According to the Intergovernmental Panel on Climate Change (IPCC), the average rate of global warming during the period 1990 to 2100 will be greater than any seen in the last 10,000 years, and much of what we now know suggests a discernible anthropogenic influence on global climate change. Not surprisingly, the effects of rapid global climate change on natural ecosystems and socio-economic dimensions have been intensely studied in recent years. The United Nations Framework Convention on Climate Change (UNFCCC), for example, states in Article 2 that:

> The ultimate objective of the Convention...is to achieve...stabilization of greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system. Such a level should be achieved with a time frame sufficient to allow ecosystems to adapt naturally to climate change, to ensure that food production is not threatened and to enable economic development to proceed in a sustainable manner.

Along with forestry, coastal resources, and the energy sector, agriculture is thought to be one of the most sensitive sectors to changing climate. Climate can have significant effects on agriculture because temperature, rainfall, and solar radiation are all major determinants of crop yields. Measurement of the vulnerability of the agricultural sector to global warming has thus been an important empirical issue. While agriculture is a relatively well-studied area compared to other sectors, however, uncertainties surrounding the economic effects of global warming on agriculture still abound. The main sources of uncertainty are: the degree of farmers' adaptation in response to climate change;

the effect of CO_2 fertilization on crop-yields; and the expected climate change across the United States. For example, warming may help regions that currently are too cold to produce the most valuable crops, even as it hurts other regions that may already be too warm to produce the most valuable crops.

My dissertation estimates the economic effects of anthropogenic-induced climate change on U.S. agriculture. The dissertation postulates from the outset that farmers optimally adapt to varying environmental conditions. Thus, land prices can be used to measure the highest value use of the land. Using this assumption, this paper attempts to extend previous research on this subject in three ways.

The first goal is to estimate the distributional effects of climate change on U.S. agriculture. Even though many researchers agree that the U.S. agricultural sector is likely to experience a shift of regional comparative advantage in response to changing climate, few studies actually quantify the distributional effects of global warming on U.S. agriculture. The main focus of my dissertation, therefore, is not only to estimate the aggregate impacts of climate change on U.S. agriculture, but also to examine how each region of the United Stated may be affected by changing climate.

Second, most researchers believe that the pattern of climate change will be uneven across the North American continent, inducing diverse effects across different regions. Instead of assuming uniform changes in climate variables (e.g., temperature and precipitation), therefore, this research takes into account the possibility of variations in climate change across the 48 contiguous United States.

Third, the dissertation accounts for the temporal aspects of anthropogenic-induced climate change. Most impact studies in the past were based on the equilibrium-doubled CO_2 General Circulation Model (GCM) scenarios in projecting the effects of global warming on US agriculture. In order to capture the time-dependent responses of the climate system and their impacts on US agriculture, however, this project uses transient climate change scenarios that allow an examination of the time-path of climate change in each U.S. county.

To estimate the impact of global warming on U.S. agriculture, some past studies have used traditional crop simulation model that estimate the effects of climate changes on crop yields and apply these results into the partial equilibrium model of agriculture. In contrast, this research employs the so-called 'Ricardian Approach' proposed by Mendelsohn et al. (1994). The Ricardian approach is, in essence, a hedonic analysis. It uses cross-sectional (or panel) data to estimate the statistical relationships between farmland prices and climatic variables, along with other control variables such as economic and soil conditions. Assuming that farmland is efficiently utilized, the farm rent each year will be equal to the net value of the best use of crops. In addition, if the market for land is competitive, the price of land is just equal to the present value of the stream of these rents. Hence, by estimating the effects of climate and other relevant variables on the value of farmland at different locations, it will be possible to capture the direct effects of climate on crop-yields as well as the optimizing behavior of farmers conditioned on the change in climate.

Applying the Ricardian approach in estimating the potential impacts of global warming on U.S. agriculture, my dissertation finds the followings:

1. The U.S. agricultural sector as a whole appears resilient enough to adapt to changing climate conditions and is expected to marginally benefit from global warming over the next 100 years.
2. Some regions, however, may be harmed due to global warming, especially if future climate changes in the way that is predicted by the Canadian Climate Model.
3. Regardless of which climate model is applied in my impact simulations, six out of ten USDA farm production regions consistently emerge as gainers as a result of human-induced climate change. Those regions include the Lake States, the Northern Plains, the Pacific Regions, the Northeast Region, the Mountain Region, and the Southeast Region. Many of them are northern regions and this result agrees with our intuitive prediction that warming may help cold regions to produce more valuable crops.
4. From a methodological point of view, the findings of my impact simulations suggest that the Ricardian approach used in my research and the traditional crop simulation model approach may complement each other; the Ricardian approach facilitates the examinations of the distributional (regional) consequences of global warming across the

nation, while the crop simulation model approach provides more detailed picture of climate change, crop-yields, and economic responses.

Now, before presenting the model used in my impact study, it will be informative to overview briefly the science of global warming and some of the past assessments of the impacts of global climate change on U. S. agriculture.

Chapter 2: Overview of Global Warming

Imagine for the moment that all the water vapor, the carbon dioxide, all the clouds, and all the other minor gases and the dust are suddenly removed from the earth's atmosphere, leaving an atmosphere of nitrogen and oxygen only. What would happen to our planet's atmospheric temperature? Under these conditions, according to a scientific calculation[1], the average annual surface temperature of the earth would be 21.2°F (-6°C) and our planet would become virtually uninhabitable. In fact, however, we're living on an Earth whose actual average annual surface temperature comes to about 59°F (15°C). The difference of 37.8°F (21°C) between the actual average surface temperature observed today and the hypothetical figure that applies when the atmosphere contains nitrogen and oxygen only is mainly due to the natural blanketing effect of greenhouse gases (water vapor, carbon dioxide, methane, and all the other minor gases). These gases absorb heat from the sun after it is radiated from the earth's surface.

The warming effect of the greenhouse gases in the atmosphere has been known since early in the 19th century when the similarity between the radiative properties of earth's atmosphere and of the glass in a greenhouse was recognized – hence the name *greenhouse effect*. Most of the greenhouse gases existed in the atmosphere long before human beings appeared on the scene. Since the Industrial Revolution started around 1750, however, human activities are gradually altering the concentration of greenhouse gases in the atmosphere, causing the surface

[1] Houghton, J.T. 1997. *Global Warming: The Complete Briefing*. Cambridge: Cambridge University Press.

temperature to be warmer than it would be otherwise, and producing the so-called *enhanced* greenhouse effect. For several thousand years before the beginning of industrialization, for example, the concentration of carbon dioxide in the atmosphere kept within about 280 parts per million by volume (ppmv). Since the Industrial Revolution, however, the atmospheric concentration of carbon dioxide has increased by 31 % to a value of over 360 ppmv. In addition, according to the IPCC's most recent report, the present carbon dioxide concentration has not been exceeded during the past 420,000 years, and the current rate of increase is unprecedented during at least the past 20,000 years.

How are human activities perturbing the atmospheric concentration of greenhouse gases? How will our planet's climate system be affected by this enhanced greenhouse effect? The Earth's climate system is powered by the input of solar energy. The climate system consists of five major components: the atmosphere, the oceans, the terrestrial/marine biosphere, the land surface, and the cryosphere (sea ice, mountain glaciers and continental scale ice sheets). These components interact with each other, determining the Earth's surface climate. The temperature of the Earth tends to adjust itself to maintain the balance between the absorption of energy from the Sun and the emission of infrared (heat) radiation from the surface-atmospheric system. When the absorbed solar energy exceeds the emission of infrared radiation to space, due to the addition of anthropogenic greenhouse gases in the atmosphere, temperatures increase, and, in so doing, the emission of infrared radiation to space increase. This, in turn, is expected to reduce the initial imbalance of the climate system, and eventually to achieve a new balance at a new and warmer temperature.

Among all of the greenhouse gases, water vapor (H_2O) is the strongest contributor to the natural greenhouse effect, but it is not directly influenced by human activities. Concentrations of the other greenhouse gases, in contrast, are directly influenced by emissions associated with the combustion of fossil fuels, by deforestation and agricultural activities, and by the production and use of various chemicals. These greenhouse gases include carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), chlorofluorocarbons ($CFCs$), and ozone (O_3). With the exception of ozone, all of the greenhouse gases that are directly influenced by human emissions become well mixed within the atmosphere, so that their concentration is almost the same everywhere and is independent of where the emissions occur.

While other gases such as methane and chlorofluorocarbons have a stronger impact per molecule, carbon dioxide (CO_2) has a larger overall impact on global warming through the sheer volume of its emissions. Currently, the total amount of carbon dioxide entering the atmosphere from human activities (the burning of fossil fuels, the changes in land use and deforestation) sums to about 7.5 thousand million tons per year, of which about 45 percent remains in the atmosphere for a century or more. The other 55 percent is taken up between the oceans and the land biota. If we ignore the effects of the chlorofluorocarbons and changes in ozone, which are difficult to quantify, carbon dioxide has contributed approximately 70 percent of the enhanced greenhouse effect to date.

Methane (CH_4) is another significant human-induced greenhouse gas. As a main component of natural gas, methane is responsible for about 24 percent of the enhanced greenhouse effect to date. Although the concentration of methane in the atmosphere is much less than that of carbon dioxide, the enhanced greenhouse effect caused by a molecule of methane is about 7.5 times greater than that of a molecule of carbon dioxide. The average lifetime of methane in the atmosphere is, however, about 9 to 15 years, much shorter than the lifetime of carbon dioxide.

Nitrous oxide (N_2O), also known as laughing gas, is another minor greenhouse gas, contributing about 6 percent of the enhanced greenhouse effect to date. It possesses long atmospheric lifetime of about 120 years. Although the chemical industry, deforestation, and agricultural practices all appear play some part, the sources leading to the increase of N_2O are not well identified.

Chlorofluorocarbons (*CFCs*) are man-made chemicals used widely as aerosol propellants and refrigerants. Once released into the atmosphere they remain for one or two hundred years before being destroyed, and could cause the depletion of stratospheric ozone layer, which absorbs solar ultraviolet radiation that would otherwise be harmful to humans and other forms of life on the earth. In addition, a *CFC* molecule added to the atmosphere has a greenhouse effect five to ten thousand times greater than an added molecule of carbon dioxide. Thus, even a small atmospheric concentration of *CFCs* could exert a significant greenhouse effect.

So, what has been the combined effect of all anthropogenic greenhouse gases to the climate system? And how would it affect the future climate? Globally speaking, it is very likely that the 1990s was the warmest decade and 1998 the warmest year since accurate records began somewhat over a hundred years ago. In its 2001 Third Assessment Report (TAR), the IPCC concludes, “there is new and stronger evidence that most of the warming observed over the last 50 years is attributable to human activities.” The report also projects that the globally averaged annual surface temperature is expected to rise by 2.5 to 10.4 °F (1.4 to 5.8 °C) over the period 1990 to 2100. This projection is higher than the 1995 projection in IPCC’s Second Assessment Report (SAR) of a rise of 1.8 to 6.3 °F (1.0 to 3.5 °C). The higher projected temperatures and the wider range of the TAR are due primarily to the lower projection of the cooling effect of sulfur dioxide (SO_2) emissions. In any case, the projected rate of global warming is believed to be much larger than the observed changes during the 20th century and is very likely to be without precedent during at least the last 10,000 years.

It might seem at first glance that a warming of about 1 °F over the 20th century and further 2.5 to 10.4 °F over the 21st century are not that much, compared with the short-term temperature changes we normally experience from night to day and winter to summer. But, it is indeed a large amount when considering the fact that global temperatures during the last ice age, which came to an end about 20,000 years ago, were only 9 to 10.8 °F (5 to 6 °C) cooler than today.

The effects of the projected climate change on the ecological, social, and economic dimensions have been intensely studied in recent decades. In particular, the potential effects of global warming on agriculture have received considerable attention because of agriculture's high sensitivity to changing climate conditions, let alone its obvious importance for human survival. In the next chapter, I review some of the previous literature on the sensitivity, adaptability, and vulnerability of the U.S. agriculture to global climate change.

Chapter 3: Literature Review[2]

Is there a role for economic analysis in view of the long time horizons and the associated uncertainties in critical natural and physical science data? Are the costs of slowing a CO_2 buildup justified by the benefits of avoided damages? Addressing these issues, Adams (1989) argues that despite problems in applying benefit-cost analysis to such long-term phenomenon as climate change, there is clearly a role for economics in climate change debates. According to Adams, even in the absence of data with which to measure correctly the costs of various policy alternatives, economics provides a useful perspective in terms of recognizing opportunity costs and framing policy questions, thus giving guidance to the natural and physical scientists in data collection. As for the effects of human-induced climate change on U.S. agriculture, Adams concludes that most qualitative evidence indicates that the U.S. will experience both regional gainers and losers, as regional comparative advantage changes in response to regional changes in climate. According to Adams, overall U.S. agricultural production appears capable of meeting projected demands. Adaptation strategies, however, may be needed to soften the negative impacts of climate change on specific regions and resources.

In many respects, the U.S. Environmental Protection Agency (EPA)'s 1989 report (Smith and Tirpak, 1989) is one of the most comprehensive climate impact studies undertaken in the United States during the past two decades. This

[2] For more complete set on literature of global climate change and agriculture, refer to Reilly, J. (Guest Editor), Climate Change, Impacts on Agriculture, *Climatic Change*, 43 (4), 645-793, 1999.

report attempts to identify the sensitivities, regional differences, national impacts, and policy implications of global climate change. The effects of global climate change on the agricultural sector, which is a part of an overall assessment of climate change impacts, is evaluated based on doubled CO_2 equilibrium climate scenarios, using three General Circulation Models (GCM) - all of which predict a nontrivial warming over the United States. The Oregon State University (OSU) model yields 3 C, Goddard Institute for Space Studies (GISS) yields 4.3 C, and Geophysical Fluid Dynamics Laboratory (GFDL) yields 5.1 C. All three models also project that annual precipitation will increase; GISS and OSU predict that annual precipitation will rise by 73 mm (2.92 inches) and 62 mm (2.48 inches), respectively, while GFDL projects a rainfall increase of only 33 mm (1.31 inches).

The basic finding of the report is that although climate change is not likely to threaten U.S. food supplies, it will affect crop yields and result in a northward shift in cultivated land, causing significant regional dislocations in agriculture with associated impacts on regional economies. Brief summaries of the 1989 U.S. EPA report on crop yields and economic impacts are as follows:

Crop Yields:

- The direct effects of climate change may reduce average yields of corn, soybeans, and wheat, except in the northernmost latitudes where warmer conditions provide a longer frost-free growing season. Decreases in yields result primarily from higher temperatures, which shorten a crop's life cycle.

- When the beneficial effects of CO_2 on crop photosynthesis and transpiration are included along with the effects of climate change, soybean and wheat yields could overcome the negative effects of climate change in some locations. If climate changes are severe, however, yields could still decline.

Economic Impacts:

- The nation's agricultural output may experience a small to moderate aggregate reduction. Production still appears to be adequate to meet domestic consumption needs.
- Assuming no change in export demand, reduced outputs would decrease exports, which could negatively affect global food supplies and the U.S. trade balance. This report, however, did not analyze global changes in agriculture.
- The economic response of agriculture to shifts in regional productivity may be to shift crop production and associated infrastructure in a northward direction. It is not possible to determine, however, if corn and soybean production could be sustained in northern areas, because soil conditions and other factors were not analyzed.

Between 1990 and 1992, a multidisciplinary team at Resources for the Future (RFF) performed a highly detailed and disaggregated study of the effects of climate change in the Missouri-Iowa-Nebraska-Kansas (MINK) region (Easterling et al., 1993). To simulate future climate change, they use an analogous climate that prevailed in the MINK region during the dust bowl of the 1930s. Relative to the climate of 1951-1980, which is used as a "control climate," the 1930's climate was on average 1 C warmer, with annual average precipitation lower by 3% to 15% in the four states. The MINK study proceeds in two major steps. First, the analogous climate is imposed on the agriculture of the region under technological and economic conditions prevailing in 1984/87. Second, the agricultural sector's characteristics are projected to the year 2030, and the analogous climate is again imposed on this changed sector. Effects of increased CO_2 concentration on both crop yield and water use are also simulated, as are a set of adjustments that farm management may select to mitigate yield loss. This approach is conducted at the level of individual farms, using some 50 representative farm enterprises across the region, each specified in great detail by soil type, local weather, and kind of production. Results for these 50 representative farms are then extrapolated and aggregated to give regional total agricultural impacts.

The simulated impacts shows that, when no account is taken of the CO_2 fertilization effect, and no on-farm adjustments are permitted, the value of MINK crop production under the analogous climate declines 17.1% from the average for 1984-87. With the fertilization effects of increased atmospheric CO_2 and on-farm adjustments, however, most of the losses are eliminated (by 80% compared to the case with no adjustment and no CO_2 enrichment). In these simulations, the CO_2 fertilization effects are more important than on-farm adjustments in moderating the effects of the analogous climate on crop yields. While the MINK study is methodologically innovative, some critics argue that the analogous climate of the 1930s used in the study is too close to today's climate conditions to simulate a useful measure of likely impacts of human-induced climate change. In addition, the adaptations (on-farm adjustments) included in the assessment are deemed too selective and, therefore, inadequate to capture fully the optimizing behavior of a farmer.

In 1994, Robert Mendelsohn, William D. Nordhaus, and Daigee Shaw, hereafter MNS, proposed the so-called "Ricardian approach" to estimate the impacts of climate change on agriculture as an alternative to what they called the "production-function approach." According to MNS, the production function approach (such as used in the MINK study) is inherently biased since it fails to take into account the infinite variety of substitutions and adaptations a farmer may take as climate conditions change. Instead of trying to measure yields of specific crops, the Ricardian approach examines how dimate in different places affects the net rent or value of farmland. Since various agricultural practices and farmland values are closely related to climate conditions, measuring the effects of climate variables on farmland values allows researchers to account for the direct impact of climate on yields of different crops as well as other potential adaptations to different climates.

Applying a uniform climate change of 5 F (2.78 C) temperature increase accompanied by an 8% increase in precipitation all across the United States, MNS present two sets of impact estimations: cropland weighted estimation and crop-revenue weighted estimation. Cropland weights (i.e., the percentage of land that is used for crops in each county) tend to emphasize grain production, which thrives in the Midwest and the relatively cool climate of the northern United States. Crop-revenue weights (i.e., the value of crops sold by each county), on the other hand, tend to emphasize the irrigated lands of the West and South that thrive in a Mediterranean and subtropical climate, and thus reflect a broader definition of agriculture. Under the cropland weights, MNS estimate that the loss in farmland values due to the projected climate change ranges from \$199 billion to \$141 billion in 1982 US dollars, without taking into account CO_2 fertilization effects. When crop-revenue weights (MNS's preferred weights) are used, however, the net impact of warming is slightly beneficial, projecting an increase of \$20-\$35 billion in farmland values. The differing results are due to the fact that the crop-revenue approach puts relatively more weight on the irrigated lands of the West and South that thrive in a Mediterranean and Subtropical climate, a climate that will become relatively abundant with global warming.

Recognizing that most of the early evaluations of the effects of climate on agriculture did not adequately account for economic adaptations, the Economic Research Service (ERS) of the USDA published a report that summarizes and synthesizes results from several studies conducted within ERS or through cooperative agreements with university collaborators (Schimmelpfennig et al., 1996). Given the uncertainties associated with climate change impacts, the ERS report identifies two distinctive methodologies for estimating climate impacts on agriculture, and it compares the strengths and limitations of the structural modeling approach (i.e., crop simulation model approach) and spatial analogue model approach (e.g., the Ricardian approach). Kaiser et al. (1993) embody the structural modeling approach and combine a crop-response model with a structural model of the management and economic decisions farmers must make, while Adams et al. (1995) and Darwin et al. (1995) exploit observed differences in agricultural production and climate among regions. According to the ERS, the following broad results have emerged from their assessment of these two approaches.

1. Climate change is not likely to disrupt the U.S. agricultural economy seriously. Most estimates suggest aggregate economic impacts of between -0.2 and 0.2 percent of gross domestic product. Farm-level adaptation will enable U.S. agriculture to mitigate most negative impacts that climate change might have on current production practices.
2. While net impacts on U.S. agriculture are likely to be small, some regional impacts could be very disruptive. Shifting production possibilities and changing economic conditions will alter the nature of competition for land and water resources among economic sectors. Resulting land-use changes will alter domestic patterns of crop and livestock production.

Using the Agricultural Sector Model (ASM) as the basic model, Adams et al. (1999) extend previous work on the impacts of climate change on agriculture by: (1) incorporating other crops such as fruits and vegetables into the regional crop alternatives for the Southeast and other southerly locations; (2) allowing for crop migrations into regions where those crops are not currently being grown; and (3) assessing the potential for technological change to offset climate change. The ASM is a spatial equilibrium model formulated as a mathematical programming problem. The production and consumption sectors are assumed to be made up of a large number of individuals, each of whom operates under competitive market conditions. The area between baseline supply and demand curves equals the baseline economic welfare. The area between supply and demand curves after a posited climate change is the new economic welfare. This study primarily uses a set of uniform climate change scenarios and two General Circulation Model (GCM) scenarios to project future climate conditions (GISS and GFDL-R30). Assuming carbon dioxide levels of 530 ppmv, these climate change scenarios are then examined for both a 1990 and a 2060 economy.

According to the simulation results, the welfare gain from a 1.5 C warming with 7 percent increase in precipitation is $55 billion, using a projected 2060 economy, and $20 billion using a 1990 economy context. A 5.0 C warming with 7 percent increase in precipitation leads to benefits of only $13 billion in 2060. The GCM-based analyses indicate that if climate changes according to the GISS forecasts, then net welfare increases by $116 billion for the 2060 economy in 1990 dollars. The GFDL-R30 analysis reveals losses of over $16 billion. These losses arise from the harsher climate conditions under the GFDL-R30. The GCM results indicate that a broader range of impacts is possible with different regional and seasonal forecasts. Climate change is also expected to alter agricultural production patterns across the United States. With a 2.5 C temperature increase accompanied by a 7 percent precipitation increase, all regions experience expansion in total crop production except for the Southern Plains and Delta States regions. In the more severe case (5 C temperature increase with no precipitation change), gains are confined to the Northeast, Northern Plains, Mountain States, and Pacific Coast, with losses observed in southern regions. The same pattern holds for both economic scenarios, except that the Northeast is much harder hit in 2060 than in 1990.

Recently, the National Assessment Synthesis Team (2001) of the US Global Change Research Program produced the most comprehensive work ever undertaken in assessing the impacts of climate change on the United States. The two primary transient climate model scenarios used in this assessment are developed at the Canadian Climate Centre (CGCM1) and the Hadley Centre in the United Kingdom (HadCM2). Both the Canadian and Hadley model scenarios project substantial warming during the 21st century. In the Canadian model scenario, increases in annual average temperature of 5.5 C by the year 2100 occur across the central US, with changes about half this large along the east and west costs. In the Hadley model scenario, the eastern US has temperature increases of

2-3 C by 2100, while the rest of the nation warms by as much as 4 C more, depending on the region.

The agriculture sector assessment considers crop agriculture, grazing, livestock, and environmental effects of agriculture. The impact study was performed using a US national Agricultural Sector Model. As mentioned before, ASM is designed to simulate the effects of various changes in agricultural resource usages or availabilities on agricultural prices, quantities produced, consumers' and producers' welfare, exports, imports, and food processing. The key findings of this assessment suggest that the net effects of climate change on the agricultural segment of the U.S. economy over the 21st century are generally positive, reflecting the generally positive-yield effects. The exceptions are simulations under the Canadian scenario (CGCM1) in the 2030 time period. Economically, consumers benefit from lower prices, while producers' profits decline. Under the Canadian scenario, these opposing economic effects are nearly balanced, resulting in a small net effect on the national economy. Under the Hadley scenario (HadCM2), producers' profits decline by up to $3 billion, while consumers save $9-12 billion. The total value of crop and livestock production is positive for all regions in both the 2030 and 2090 time frame under the Hadley scenario. In contrast, this economic index differs among regions under the Canadian scenario in both the 2030s and 2090s. It is positive for most northern regions, mixed for the northern Plains, and negative for Appalachia, the Southeast, the Delta States, and the southern Plains.

Regardless of which methodology is used, the following points of consensus seem to have emerged on the potential effects of global warming on U.S. agriculture from these assessments during the past two decades.

1. The aggregate impacts of greenhouse-gas-induced climate change on U.S. agriculture are expected to be minimal, even slightly beneficial over the next 50 to 100 years.
2. The effects, however, will be uneven across the United States, resulting in a shift of regional comparative advantage for U.S. agriculture in response to changing climate.
3. The estimated effects tend to be sensitive to climate change scenarios used in the impact study (e.g., uniform climate change scenario, doubled CO_2 equilibrium climate scenario, or transient climate change scenario).

Various methodologies used in the impact studies reviewed here have their own strengths and weaknesses, as will be explained in detail in the next chapter. Preferably, an agricultural impact study should be able properly to take into account a farmer's optimizing behavior to changing climate conditions, using time-dependent transient climate change scenarios, and attempt to quantify the regional impacts as well as the overall impacts of climate change. In my opinion, the National Assessment Synthesis Team (NAST) work most closely lives up to these criteria. Since the NAST study is primarily based on the crop simulation model approach, it will be interesting to compare its results with my impact study, and to observe how both approaches can complement each other.

Chapter 4: Methodology and Model Specifications

METHODOLOGY

Broadly speaking, two distinctive methods have emerged to assess the potential economic impacts of climate change on agriculture: an agronomic production function approach and a Ricardian approach. Each approach has its own strengths and weaknesses. The agronomic production function approach predicts changes in yields from various crop simulation models such as Crop Environment Resource Synthesis (CERES) or Soybean Growth Simulation Model (SOYGRO) and then applies these predictions in partial equilibrium economic models of agriculture. The agronomic approach has been popular in climate impact research because of its ability (1) to capture the extensive detail of specific crop models, (2) to integrate the links between climate change, crop yields, and market equilibrium, and (3) to estimate changes in market prices and distributional effects on producers and consumers. The major weakness of this approach, however, is that the various degrees of adaptations farmers might take in response to climate change are hard to incorporate into the models. They may thus overestimate the vulnerability of agricultural sector to climate change.

The Ricardian approach, on the other hand, relies on empirical cross-sectional (or panel) data and examines how farmland prices vary across geographic locations with different climates. One can then use the estimated coefficients to simulate the economic effects of climate change. The strength of this relatively new approach is that it implicitly accounts for farmers' optimizing behavior in response to changing climate. The Ricardian approach, however, has been criticized on the ground that it typically ignores likely changes in output and input prices, which in turn affect farm-level adaptation decisions in response to climate change. As mentioned in Chapter 1, I've adopted the Ricardian approach in my impact study, and in the rest of this chapter, I address some of theoretical issues regarding the Ricardian approach.[3]

Assume that consumers have a well-behaved system of inverse demand functions as follows:

$$p_1 = D^{-1}(q_1, q_2, ..., q_I, y)$$
$$\cdot$$
$$\cdot$$
$$\cdot$$
$$p_I = D^{-1}\left(q_1, q_2, ..., q_I, y\right)$$

where p_i = the price of good i ($i = 1,\ldots, I$)
q_i = the quantity of good i ($i = 1,\ldots, I$)
y = aggregate income

Also assume that a set of production functions link various inputs (including environmental inputs) to the production of outputs by a farm on a certain site, as follows:

[3] The bulk of following analysis follows Mendelsohn *et al*. (1999).

$$q_i = q_i\left(\mathbf{K_i}, \mathbf{E}\right), \quad i = 1,\ldots,I$$

where $\mathbf{K_i} = [k_{i1},\ldots, k_{ij},\ldots, k_{iJ}]$, where
k_{ij} = purchased input j ($j = 1,\ldots,J$) in the production of good i
$\mathbf{E} = [E_1,\ldots,E_m,\ldots E_M]$, where
E_m = an exogenous environmental input m (e.g., climate) into the production of goods ($m = 1,\ldots,M$)

Note that the environmental inputs (**E**) are the same for the production of any different goods at any particular production site. The above production function simply describes how a farmer can produce a certain amount of output (e.g., crop), given the purchased inputs ($\mathbf{K_i}$) and environmental inputs (**E**). Now, given a set of input price, R_j, for input K_j ($j = 1,\ldots, J$), the exogenously-determined environmental inputs, and the production function, cost minimization leads to the following cost function:

$$C_i = C_i\left(q_i, \mathbf{R}, \mathbf{E}\right)$$

Here, C_i is the cost of production of good i, input prices are $\mathbf{R} = [R_1,\ldots,R_J]$, and $C_i(\cdot)$ is the cost function. The cost function indicates the total cost to the farmer of producing output q_i, given the prices of purchased inputs and given the environmental factors. At this point, it is convenient to separate land from the other inputs, **K**, and assume that land, L_i is heterogeneous in environmental characteristics **E** with an annual cost or rent of P_L. Hence, firms' (farmers') profit-maximization problem is to solve:

$$\underset{q_i}{Max}\ p_i q_i - C_i\left(q_i, \mathbf{R}, \mathbf{E}\right) - P_L L_i$$

If we assume that the market for land is perfectly competitive, economic profits will be driven to zero such that:

$$p_i q_i - C_i\left(q_i, \mathbf{R}, \mathbf{E}\right) - P_L L_i = 0$$

Solving for the value of land rent per acre, therefore, yields:

$$P_L = \frac{\left[\, p_i q_i - C_i\left(q_i, \mathbf{R}, \mathbf{E}\right)\right]}{L_i}$$

In other words, the equilibrium market rent on the land should be equal to the net revenue from the land. Now, taking the present value of this stream of net revenue over time, we obtain the following equation, which indicates that the value of land (V_L) is equal to the present value of the stream of future net revenue (assuming equilibrium prices remain constant into the future):

$$V_L = \int_0^\infty P_L e^{-rt} dt = \int_0^\infty \frac{\left[\, p_i q_i - C_i\left(q_i, \mathbf{R}, \mathbf{E}\right)\right] e^{-rt}}{L_i}\, dt$$

The essence of the Ricardian approach is captured in the above equation; a change in any environmental factor (in **E**) affects production and costs, which in turn affect a farmer's optimizing behaviors, affecting net revenue and land values. By examining how land values shift with changes in the climate conditions, therefore, one can estimate the impact of climate change through changes in the present value of net revenue. If climate change is beneficial (or harmful) to farming, it will increase (or decrease) net revenue and thus land values.

The Ricardian model discussed so far assumes that the market prices of inputs (e.g., labor, fertilizer) and outputs (e.g., cotton and soybean prices) remain constant. This is rather a strong assumption. Climate change may lead to increases in the supply of some crops (heat-loving plants such as citrus) and decreases in the supply of others (cool-loving plants such as winter wheat). In a global-warming scenario, it is reasonable to believe that the prices of heat-loving plants will tend to fall due to supply expansion, while those of cool-loving plants will tend to rise. According to Mendelsohn *et al*. (1996), however, this potential bias of a Ricardian approach in estimating the effect of climate change on agriculture does not seem to be substantial. We now discuss the empirical model actually used in my estimations.

MODEL SPECIFICATIONS

A number of climatic, soil-related, and economic factors influence crop-yields and the productivity of the agricultural sector. The Ricardian approach is, in essence, a hedonic analysis that uses cross-sectional (or panel) data to estimate the statistical relationships between farmland prices and climatic variables, along with other control variables such as economic and soil conditions.[4] We take the level of the county in the 48 contiguous U.S. states as the unit of observation (approximately 3,000 counties). Then pooled data for these counties over three

[4] The effects of land taxes on the value of farmland are not considered in this model. For interesting survey and discussion on the effects of land taxes, see Mieszkowski, P and G. Zodrow (1989).

time periods (1982, 87, 92) - a total of about 9,000 observations - are used to estimate the following model:

$$
\begin{aligned}
\ln V_L = a + \sum_{s=1}^{4} b_s T_s + \sum_{s=1}^{4} b'_s T_s^2 + \sum_{s=1}^{4} g_s P_s + \sum_{s=1}^{4} g'_s P_s^2 + \sum_{s=1}^{4} d_s D_s + \sum_{s=1}^{4} h_s SR_s \\
+ \sum_{s=1}^{4} q_s RH_s + \sum_{i=1}^{types} l_i Soil_i + \sum_{i=1}^{vbles} m_i Z_i + \sum_{i=1}^{regions} v_i RD_i + \sum_{i=1}^{years} r_i YD_i + e
\end{aligned}
$$

where $\ln V_L$ = natural logarithm of the value of farmland per acre
T_s, T_s^2 = temperature and its square term [s = 1 (spring), 2 (summer), 3 (fall), 4 (winter)]
P_s, P_s^2 = precipitation and its square term
D_s = daily temperature change
SR_s = solar radiation
RH_s = relative humidity
$Soil_i$ = soil characteristics (e.g., organic matter), $i = 1, \ldots, types$
Z_i = socio-economic and geographic control variables (e.g., population density per county, elevation), $i = 1, \ldots, variables$
RD_i = dummy variables for USDA farm production regions
YD_i = dummy variables for year 1982, 1987

The functional form I've chosen for the baseline regression is semi-log form, taking the natural logarithm of the dependant variable (farmland value). Hence, each estimated coefficient represents the predicted percentage change of the value of farmland per acre given a unit change of an explanatory variable. The total number of explanatory variables included in the regression is 52, of which 28 are climate-related. Since the original climate variables are measured by a monthly term rather than a seasonal term, I've average them in a following way to obtain seasonal climate patterns.[5]

[5] From the general circulation models employed later, I obtain projections of climate (i.e., temperature, precipitation, daily temperature range) for each of the four seasons. Since I want to

Spring Climate = average of March, April, and May.

Summer Climate = average of June, July, and August.

Fall Climate = average of September, October, and November.

Winter Climate = average of December, January, and February.

The remaining 24 control variables are intended to capture socio-economic factors, geographic (regional) factors, and period effects, as well as the influences of soil-related variables. The socio-economic variables include population density per county, county-level value of output, and income per capita. The variables representing soil quality include cropland capability class, potential conversion to cropland, organic matter, available water capacity, permeability, clay, and universal soil loss equation (USLE) for cropland. In the baseline regression, the year 1992 is taken as the base year, and two yearly dummy variables are included in the regression for the year 1982 and 1987. In addition, taking the Southern Plains (Texas and Oklahoma) as the reference region, 9 USDA farm production regional dummy variables are included in the regression to reflect regional differences not captured by climate or other control variables included in the model. These regional dummies represent the following states:

- The Pacific Region (WA, OR, CA)
- The Mountain Region (MT, ID, WY, NV, UT, CO, AZ, NM)

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use the climate projections times the estimated coefficients to predict change in land prices, I need the regression to estimate a coefficient for each of the four seasons.

- The Northern Plains (ND, SD, NE, KS)
- The Lake States (MN, WI, MI)
- The Corn Belt (IA, IL, MO, IN, OH)
- The Delta States (AR, LA, MS)
- The Northeast Region (ME, NH, VT, RI, CT, NJ, DE, MA, PA, MD, NY)
- The Appalachian Region (WV, VA, KY, TN, NC)
- The Southeast Region (AL, GA, SC, FL)

All nominal variables in the model are converted into 1996 constant dollars using the GDP deflator. The square terms of some of the climate variables are included in the model in order to capture the nonlinear influences of those climate variables on farmland values. The model has also been adjusted so that the coefficients of the linear terms of each climate variable can be interpreted as the marginal effect of that variable (in percentage terms) on per acre farm values evaluated at the sample mean for the U.S.[6] The baseline regression is weighted, using total crop revenue in each county, so that the regression adequately accounts for those counties that are important to total agricultural production in the United States. In the next Chapter, I describe in more detail the dataset used in my baseline regression. The results of the baseline regression are presented in Chapter 6.

[6] For the square terms of temperature and precipitation, before squaring, I first subtract the mean and then square the variables. As a result, the coefficients of the linear terms of temperature and precipitation represent the marginal effects on per acre farm values evaluated at the sample mean for the U.S.

Chapter 5: Data

A number of climatic, soil-related, and economic factors influence crop-yields and the productivity of the agricultural sector. Taking the level of the county as a unit of observation, the following pooled data will be used to estimate the model. Color maps of the U.S. are provided in Appendix Figure A to visualize the spatial datasets described in this chapter.

I. Climate variables:

a) 30-year average precipitation for each month in mm (1961-1990):

The 30-year average precipitation for each month is calculated by summing the daily precipitation for each month, and then all monthly amounts over the 1961-1990 period for each month are summed and divided by 30. It is well recognized among climatologists and hydrologists that spatially reliable measurement of precipitation is hard to acquire because of the complex topographic nature of climate, especially in mountainous areas. Thanks to almost 6 years of joint work between the USDA Natural Resources Conservation Service (NRCS) and the Spatial Climate Analysis Service (SCAS) at Oregon State University (OSU), however, high-spatial-resolution precipitation maps (a resolution of approximately 4km) are now available for the whole United States. Some of the input used to produce these state-of-the-art maps include 1961-90 mean monthly precipitation data for each month from over 8000 National Oceanic and Atmospheric Administration (NOAA) Cooperative sites and selected state network stations. Since the initial dataset obtained from the NRCS consists of extremely high spatial resolution, I apply a Geographic Information System (GIS) tool to derive county averages.[7]

b) 30-year average temperature, and average daily (diurnal) temperature range, for each month in °C (1961-1990):

The 30-year average monthly temperature represents temperature averaged over the 1961-1990 period for each month. Daily temperature range measures the difference between the maximum and minimum daily temperature. Average daily minimum temperature for each month is calculated by summing the daily minimum temperatures for an individual month and dividing by the number of days used in the summation for that month. The monthly averages over the period of 1961-1990 are then summed and divided by 30 to obtain 30-year average daily minimum temperature for each month. The 30-year average daily maximum temperature for each month is similarly calculated. The 30-year average daily temperature range for each month is simply the difference between the 30-year daily minimum and maximum for each month. I obtain the state-of-the art spatial temperature datasets (both average and daily range) from the USDA Natural Resources Conservation Service (NRCS) and the Spatial Climate Analysis Service (SCAS) at Oregon State University (OSU), and then use a GIS tool to generate county averages.

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[7] I am grateful to Dr. Phil Pasteris at the NRCS National Water & Climate Center, USDA for his helpful comments on the derivations of county averages of temperature and precipitation.

c) Monthly Solar Radiation (Kilojoule, kj) and Relative Humidity (%):

The original dataset on solar radiation and relative humidity is obtained from the Vegetation-Ecosystem Modeling Analysis Project (VEMAP). The VEMAP is a multi-agency program to simulate and understand ecosystem dynamics for the continental United States. The VEMAP generates both monthly total incident solar radiation at the surface (kj^{-1}) and monthly mean daylight relative humidity (%) from 1895-1993 climate history of the United States on a 0.5° grid, and I average them at a county level, using a GIS package.

II. **Farmland value and economic, demographic variables:**

Data on farmland value and economic, demographic variables are obtained from "USA Counties 1998 CD-ROM" produced by U.S. Bureau of the Census. This CD-ROM contains a collection of data from the Bureau of the Census and other federal agencies, such as the Bureau of Economic Analysis or the Bureau of Labor Statistics. These files provide data for the United States, 50 States and the District of Columbia, and 3,142 counties or county equivalents defined as of January 1, 1992 (3,194 areas in all).

a) Average dollar value of farmland and buildings per acre for each county in 1982, 1987, and 1992:

Respondents (farmers) were asked by U.S. Bureau of Census to report their estimate of the current market value of farmland and buildings owned, rented, or leased from others, and rented or leased to others. Market value refers to the respondent's estimate of what the land and buildings would sell for under current market conditions (if the value of farmland and buildings was not reported, it was estimated during processing by using the average value of farmland and buildings from a similar farm in the same geographic area).

b) Value of farm products (crops) sold from each county in $thousands in 1982, 1987, and 1992:

Value of farm products (crops) sold represents the gross market value before taxes and production expenses. It includes sales by the operator as well as the value of any shares received by partners, landlords, contractors, or others associated with the operation. In addition, it includes receipts from placing commodities in the Commodity Credit Corporation (CCC) loan program. It does not include payments received for participation in Federal farm programs, nor does it include income from farm-related sources such as custom work and other agricultural services, or income from nonfarm sources. Data may include sales from crops produced in earlier years and exclude some crops produced in a given year, but held in storage.

c) Total cropland in acres within each county in 1982, 1987, and 1992:

Cropland consists of land from which crops were harvested or hay was cut; land in orchards, citrus groves, vineyards, nurseries, and greenhouses; cropland used only for pasture or grazing; land in cover crops, legumes, and soil-improvement grasses; land on which all crops failed; land in cultivated summer fallow; and idle cropland. The data on total cropland within each county is used in impact simulations later on.

d) Per capita personal income of each county - annual personal income per person in $1,000 in 1982, 1987, and 1992:

Per capita personal income of a county is defined as the personal income of all the residents of a county divided by the resident population of the county. It is based on resident population enumerated as of April 1 for decennial census years and estimated as of July 1 for other years. The personal income of a county is defined as the income received by, or on behalf of, all the residents of that county. It consists of the income received by persons from all sources, that is, from participation in production, from both government and business transfer payments, and from government interest. Personal income is the sum of wage and salary disbursements, other labor income, proprietors' income, rental income of persons, personal dividend income, personal interest income, and transfer payments, less personal contributions for social insurance.

e) Population density of each county - number of thousands of people per square mile in 1982, 1987, and 1992:

Persons per square mile are the average number of inhabitants per square mile of land area. These figures are derived by dividing the total number of residents by the number of square miles of land area in the specified geographic area. Figures for 1982 and 1992 are based on a complete, or 100-percent count of population as of April 1, for year 1980 and 1990, respectively. I approximate the population density for year 1987 by taking the average population density of 1982 and 1992.

f) County-level earnings in all industries in 1982, 1987, and 1992:

Total earnings cover wage and salary disbursements, other labor income, and proprietors' income. Total earnings include, among others, farm earnings, earnings in agricultural services, earnings in mining, earnings in construction, earnings in manufacturing, earnings in transportation and public utilities, earnings in wholesale trade, earnings in retail trade, earnings in services, and earnings in finance, insurance, and real estate.

III. Soil-related variables:

I obtain all of the initial datasets on soil-related variables from the 1992 National Resource Inventory (NRI).[8] The NRI, produced at 5-year intervals by the USDA's Natural Resources Conservation Service (NRCS), is the most comprehensive database ever assembled on natural resources of the nonfederal lands of the United States (approximately 74 percent of the nation's land area). The 1992 NRI database includes data from three inventory years, 1982, 1987, and 1992. Its focus is on soil, water, and related resources of farms and nonfederal forests and grazing lands. Since the 1992 NRI database contains almost a million sample points nationwide, rather than by county, I use a statistical package to

[8] I thank Fort Worth Federal Center, TX, NRCS, USDA for generously providing me four CD set of 1992 National Resource Inventory (1992 NRI).

generate the average values of the following seven variables (a through g) for each county, taking the expansion factor (XFACT) in the NRI data field as a weight. [9] The expansion factor specifies the number of 100 acres that a sample point represents in the NRI database. When summed over all sample points in a given county, it equals the total nonfederal land area of the county. Thus, the weighted average of each variable at a county level is computed as:

$$S_n = \frac{\sum_p \left(S_{p\mathrm{n}} \times XFACT_{p\mathrm{n}} \right)}{\sum_p XFACT_{pn}}$$

where $S_n =$ Average value of variable S for county n

$S_{p\mathrm{n}} =$ Value of variable S at sample point p of county n

$XFACT_{p\mathrm{n}} =$ Expansion factor of sample point p of county n

$\sum_p XFACT_{pn} =$ Total nonfederal land area of a county n (in 100 acres)

a) Capability Class in 1982, 1987, and 1992:

Land capability classification is a system of grouping soils primarily on the basis of their capability to produce common cultivated crops and pasture without deteriorating over a long period of time. The "capability class" is the broadest category in the land capability system. Class codes ranging from 1 to 8 are used to represent both irrigated and non-irrigated land capability classes. The

[9] I thank Daniel Hellerstein at ERS, USDA for his helpful comments. I especially thank Henry Bogusch at NRCS, USDA for kindly crosschecking and validating some of the sample county averages I derived from Soil Database and NRI database.

numerals indicate progressively greater limitations and narrower choices for practical use. The classes are defined as follows:

- Class 1: Soils have few limitations that restrict their use.
- Class 2: Soils have moderate limitations that reduce the choice of plants or that require moderate conservation practices.
- Class 3: Soils have severe limitations that reduce the choice of plants or that require special conservation practices, or both.
- Class 4: Soils have very severe limitations that reduce the choice of plants or that require very careful management, or both.
- Class 5: Soils have little or no hazard of erosion but have other limitations, impractical to remove, that limit their use mainly to pasture, range, forestland, or wildlife food and cover.
- Class 6: Soils have severe limitations that make them generally unsuitable for cultivation and that limit their use mainly to pasture, range, forestland, or wildlife food and cover.
- Class 7: Soils have very severe limitations that make them unsuitable for cultivation and that restrict their use mainly to grazing, forestland, or wildlife.
- Class 8: Soils have limitations that nearly preclude their use for commercial crop production and limit their use to recreation, wildlife, or water supply or for aesthetic purposes.

b) Potential for Conversion to Cropland in 1982, 1987, and 1992:

The NRCS determined the potential for conversion to cropland for all sample points not classified as urban and built-up, rural transportation, water, or cropland. The NRCS' determinations were based on the likely farming conditions of the next 10 to 15 years. The NRI numerally coded potentials for conversion for 1982, 1987, and 1992 as follows:

- No likelihood of conversion to cropland (0).
- Conversion to cropland is unlikely in the next 10 to 15 years (1).
- Conversion to cropland is likely in the foreseeable future (2).
- Very likely to be converted to cropland (3).

c) Proportion of cropland that has irrigation source in 1982, 1987, and 1992:

The NRI determined irrigation for the year or years of cropland or pastureland cover/use. According to the NRI, the presence of irrigation source was defined as evidence of a field irrigated during the year of the inventory or having been irrigated at least 2 of the past 4 years. The NRI coded the data according to source of irrigation water as follows:

- No irrigation source (0).
- Well (1).
- Pond, lake, or reservoir (2).

- Stream, ditch, or canal (3).
- Lagoon or other waster water (4).
- Combination (5).

Based on these data, I assign zero values to sample points that have no irrigation source and the value of one otherwise. Hence, the resulting county average represents the proportion of land that has at least one irrigation source, such as pond, stream, or combination, for example.

d) Organic Matter:

Soil organic matter is the fraction of the soil composed of anything that once lived. The estimated content of organic matter is expressed as a percentage, by weight, of the soil material that is less than 2 millimeters in diameter. It includes plant and animal residue in various stages of decomposition, cells and tissues of soil organisms, and substances from plant roots and soil microbes. According to soil scientists, organic matter is perhaps the single most important indicator of soil quality and productivity because of the following reasons: (1) it aids the growth of crops by improving the soil's ability to store and transmit air and water; (2) it stores and supplies such nutrients as nitrogen, phosphorus, and sulfur, which are needed for the growth of plants and soil organisms; (3) it stabilizes and holds soil particles together, thus reducing the hazard of erosion; (4) it maintains soil in an un-compacted condition with lower bulk density.[10]

[10] *Soil Quality Information Sheet* by the National Soil Survey Center in cooperation with the Soil Quality Institute, NRCS, USDA, and the National Soil Tilth Laboratory, Agricultural Research Service, USDA, April 1996.

e) Available Water Capacity:

Available water capacity (or water-holding capacity) is an important attribute of soil that measures soil's ability to store and release available water to plants. Water-holding capacity is stated in inches of water per inch of soil. Plant-available water capacities are a required input for nearly all crop simulation models.[11] In areas where drizzle falls daily and supplies the soils with as much or more water than is removed by plants, available water capacity is of little importance. In area where plants remove more water than the amount supplied by precipitation, however, the amount of available water that soil can supply may be critical. Therefore, available water capacity is also an important factor in the choice of plants or crops to be grown and in the design and management of irrigation systems.

f) Universal Soil Loss Equation (USLE) in 1982, 1987, and 1992:

Developed in the late 1950s, the USLE is designed to predict long-term average soil loss by water erosion. Soil erosion data were not collected for sample points classified as forest land, permanent snow and ice fields, urban and built-up, rural transportation, or water areas. The USLE estimates are expressed in terms of tons/acre/year, and the multiplicative form of the equation is $A=R\times K\times L\times S\times C\times P$, where: A is the computed soil loss per unit area over a specified time; R factor describes the kinetic energy produced by the frequency and intensity of rainfall that can erode unprotected soils; K factor indicates the inherent susceptibility of a

[11] Board on Agriculture, National Research Council. 1993. Chapter 5. Monitoring and managing soil quality. *In* Soil and Water Quality: An Agenda for Agriculture. Washington D.C.: National Academy Press.

soil to erosion (higher the value, the more susceptible the soil is to erosion by water); L factor represents the length in feet from where runoff begins to the point of concentration or point of deposition of sediment carried by the runoff; the S factor describes the gradient in percent of the land slope through the point. The remaining two factors reflect the effects of human activities on erosion rates: soil cover and management practices (C) and supporting conservation practices (P).[12]

g) Permeability (Infiltration):

Permeability indicates the quality of soil that enables water to move downward through the profile. Permeability is measured as the number of inches per hour that water moves down through the saturated soil. Soil permeability is considered very slow if it is less than 0.06 inch/hour, and very rapid if more than 20 inches/hour. If water permeability is restricted or blocked, water does not enter the soil, and it either ponds on the surface or runs off the land. Thus, less water is stored in the soil profile for use by plants. Runoff can carry soil particles and surface applied fertilizers and pesticides off the field. These materials can end up in streams and lakes or in other places where they are not wanted.[13]

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[12] *National Resources Inventory Training Modules* by USDA Natural Resources Conservation Service, November 1994.

[13] *Soil Quality Information Sheet* by the National Soil Survey Center in cooperation with the Soil Quality Institute, NRCS, USDA, and the National Soil Tilth Laboratory, Agricultural Research Service, USDA, January 1998.

IV. **Other relevant variables:**

a) Elevation (m):

The average height of the county from sea level (in meter) is derived from the VEMAP dataset. The original VEMAP dataset contains average elevation for each 0.5° grid covering the continental United States. I match the geographic center of each county with the elevation of each grid cell to extrapolate the average elevation of each county.

Chapter 6: Baseline Regression

We now discuss the results of the baseline regression. As noted in chapter 4, a semi-logarithmic functional form is used in the baseline regression, taking the natural logarithm of the dependant variable (farmland value per acre). The regression coefficients are estimated by ordinary least squares (OLS), and the reported standard errors in Table 6.1 are adjusted for serial correlation and heteroskedasticiy.[14] The total number of observations actually used in the regression is 7842, due to missing data for some of the explanatory variables.[15] Each observation is weighted by total crop revenue in each county. As shown in Table 6.1, the overall fit of the model is quite good, with an adjusted R^2 of 0.82.

As mentioned in chapter 4, the model is adjusted so that the coefficients of the linear terms of each climate variable can be interpreted as the marginal effect of that variable (in percentage terms) on per acre farm values evaluated at the sample mean for the U.S. All of the precipitation variables except the linear one for winter are significant at the 15% significance levels or better. With the exception of spring precipitation, the signs on the estimated coefficients of the precipitation variables are negative.

[14] The usual OLS standard errors are not reliable because observations across the 3 time periods within the same county are likely to be correlated in this pooled OLS regression. Therefore, the standard errors and test statistics should be adjusted for cluster correlation.

[15] As mentioned previously, we take the level of county in the 48 contiguous U.S. states as the unit of observation (approximately 3,000 counties), and then data for these counties over three time periods (1982, 87, 92) are pooled together for the baseline regression.

Table 6.1: Baseline Regression

Number of obs = 7842
F(52, 2710) = 306.72
Prob > F = 0.0000
Adj. R-sq = 0.8174
No. of Clusters (FIPS) = 2711

Dependable Variable: Ln (Farmland value per acre)	**Coef.**	**Robust Std. Error.**	**t**	**P>|t|**
Precipitation (Spring)	.0059721	.0021171	2.82	0.005
Precipitation (Summer)	-.0028995	.00178	-1.63	0.103
Precipitation (Fall)	-.0024269	.0016617	-1.46	0.144
Precipitation (Winter)	-.0002181	.0014569	-0.15	0.881
Precipitation Sq. (Spring)	-.0001115	.0000269	-4.14	0.000
Precipitation Sq. (Summer)	.0000318	.0000252	1.26	0.207
Precipitation Sq. (Fall)	-8.59e-06	.0000292	-0.29	0.769
Precipitation Sq. (Winter)	.0000212	7.80e-06	2.72	0.007
Temperature (Spring)	-.0961798	.0417862	-2.30	0.021
Temperature (Summer)	-.0046084	.0424746	-0.11	0.914
Temperature (Fall)	.1710329	.0523944	3.26	0.001
Temperature (Winter)	-.0618339	.0261297	-2.37	0.018
Temperature Sq. (Spring)	-.0092972	.0037914	-2.45	0.014
Temperature Sq. (Summer)	.0063431	.0040424	1.57	0.117
Temperature Sq. (Fall)	.008531	.0063522	1.34	0.179
Temperature Sq. (Winter)	.0018745	.0015737	1.19	0.234
Daily Tem. Range (Spring)	.1593212	.056391	2.83	0.005
Daily Tem. Range (Summer)	-.1811581	.0500227	-3.62	0.000
Daily Tem. Range (Fall)	.1538146	.0498214	3.09	0.002
Daily Tem. Range (Winter)	-.2369633	.0363744	-6.51	0.000
Solar Radiation (Spring)	.0000389	.0000531	0.73	0.464
Solar Radiation (Summer)	-.0000455	.0000512	-0.89	0.374
Solar Radiation (Fall)	.000034	.0000826	0.41	0.681
Solar Radiation (Winter)	.0001386	.0000643	2.16	0.031
Relative Humidity (Spring)	-.0085737	.0081949	-1.05	0.296
Relative Humidity (Summer)	.0007835	.0086411	0.09	0.928
Relative Humidity (Fall)	.0266782	.0089123	2.99	0.003
Relative Humidity (Winter)	-.0114938	.0046321	-2.48	0.013
Ln(County’s Aggregate Earnings)	.09121	.0126676	7.20	0.000
Ln(Income per capita)	.1910014	.0895534	2.13	0.033
Population Density	.0004066	.0001267	3.21	0.001
Population Density Sq.	-6.20e-08	2.94e-08	-2.11	0.035
Cropland Capability Class	-.095475	.0326862	-2.92	0.004
Potential for Cropland	-.3099726	.0660881	-4.69	0.000
Prop. of county Land Irrigated	.7372956	.113195	6.51	0.000
Elevation	4.55e-06	.0001566	0.03	0.977
Organic Matter	.0233642	.0151731	1.54	0.124
Available Water Capacity	1.557094	.7004264	2.22	0.026
Permeability	.0253166	.0087022	2.91	0.004
USLE (Cropland)	.0060038	.0031618	1.90	0.058
Clay	-.0030535	.0018063	-1.69	0.091
Appalachian	.2867479	.0943539	3.04	0.002
Corn Belt	.3620154	.0813308	4.45	0.000
Delta States	-.2015983	.0990446	-2.04	0.042
Lake States	.3185659	.0829779	3.84	0.000

Mountain Region	.3060548	.1373973	2.23	0.026
Northern Plains	-.0107145	.0787503	-0.14	0.892
Northeast Region	.5369831	.1074455	5.00	0.000
Pacific Region	.9433049	.2990002	3.15	0.002
Southeast Region	-.1778087	.1152726	-1.54	0.123
Year 1982	.4786166	.0234996	20.37	0.000
Year 1987	.006213	.0123576	0.50	0.615
Constant	1.439978	1.931814	0.75	0.456

Thus, on average, more precipitation in spring increases farm values while increased precipitation in all other seasons is harmful to farming. The results of the regression also indicate that higher average temperature in fall increases farm values dramatically, whereas higher temperature in spring, summer, and winter reduces values. All temperature variables are significant at 5% or better, except for that of summer temperature. All of the estimated coefficients of daily temperature range are found to be highly significant. The signs of coefficients on spring and fall daily temperature variations are positive, whereas those for summer and winter temperature variables are negative.

When tested as a group, the solar radiation coefficients are significantly different from zero (F-statistic = 5.44). The effect of increased solar radiation appears beneficial for farming in spring, fall, and winter. In contrast, increased solar radiation during the summer season reduces farm values. During spring and winter, increases in relative humidity appear to have negative effects on farming, while in summer it seems to have no effect on farm values. Increases in fall relative humidity, however, appear highly beneficial. Table 6.2 summarizes the signs and magnitudes of the 3 sets of coefficients of the climate variables that will be used in the impact simulations.

Table 6. 2: Estimated Marginal Effects of Each Climate Variables

Variable	**Marginal Effect on Farm Values per mm/monthly Change**
Spring Precipitation	0.60%
Summer Precipitation	-0.29%
Fall Precipitation	-0.24%
Winter Precipitation	-0.02%
Variable	**Marginal Effect on Farm Values per 1° C Change**
Spring Temperature	-9.62%
Summer Temperature	-0.46%
Fall Temperature	17.10%
Winter Temperature	-6.18%
Variable	**Marginal Effect on Farm Values per 1° C Change**
Spring Daily Temperature Range	15.93%
Summer Daily Temperature Range	-18.12%
Fall Daily Temperature Range	15.38%
Winter Daily Temperature Range	-23.70%

Overall, the derivatives of the other control variables exhibit expected signs. Farm values rise with increases in population density (but at a decreasing rate), income per capita, and county-level aggregate output, all of which represent non-agricultural pressure on the values of farmland.[16] As expected, the coefficients of cropland capability class and non-agricultural land's potential conversion to cropland exhibit negative signs.[17] Organic matter, available water capacity, and permeability coefficients are significant at 15% or better and positive, whereas the effect of clay is harmful to farm values. The coefficient of

[16] A county is an open economy, so the value of income is not necessarily the same as the value of output.

[17] Remember that the number of cropland capability class, ranging from 1 to 8, indicates progressively greater limitations and thus narrower choices for agricultural use. The coefficient on non-agricultural land's potential conversion to cropland is also negative because those lands exert a competitive pressure on the price of farmland.

Elevation, on the other hand, is not significantly different from zero. Not surprisingly, an increase in the proportion of land that is irrigated has a highly beneficial effect on the value of farmland. Curiously, the coefficient on Universal Soil Loss Equation (USLE) for cropland exhibits a positive sign. This may be due to the fact that valuable farmland tends to be more extensively utilized, making it more susceptible to soil erosion.

The coefficients of the regional dummy variables are significant at the 15% or better, with the exception of the one for the Northern Plains. The value of farmland in the Northern Plains, therefore, must be similar to that of the reference region, Southern Plains. The results indicate that all regions except the Delta States and the Southeast region have higher farm values than those of the Southern Plains, other things being equal. The coefficient for year 1982 is quite significant and positive relative to the base year, 1992, whereas the coefficient for year 1987 is not significantly different from zero (i.e., from 1992).

Figure 6.1 depicts the spatial contribution of current climate conditions to the values of farmland across the contiguous United States, after controlling for the influences of non-climatic variables used in the baseline regression. The map shown in 6.1 is constructed by first calculating, for each climate variable, the deviation between each county and the U.S. sample mean. These deviations are then multiplied by the estimated climate coefficients and then summed across the climate variables. The result is that counties with positive values are endowed with climate that yields above-average farmland values, or vice versa, in percentage terms relative to the U.S. national average. When the effects of all climate variables are taken together, the most favorable climates are around the Corn Belt, the Southeast Region, lower parts of the Northeast Region, the Delta States, the Appalachian Region and the west coastal area of the Pacific Region. On the other hand, the poorly-endowed regions in terms of climates include most of the Mountain Region, the Northern Plains, some part of the Southern Plains, the upper Lake States, and upper New England. As an example, Table 6.3 and 6.4 show the counties with the most valuable climates and the least valuable climates in farm values per acre across the United States.

Note that while some areas such as central California produce the highest-value agricultural output, the map shown in Figure 6.1 does not show those counties to have the largest boost from their climate. Instead those counties produce valuable output because of the effects of non-climate variables in Table 6.1 such as % of county land irrigated.

Applying the estimated coefficients of climate variables in the baseline regression to the projected climate change scenarios, we can now simulate the potential effects of human-induced climate change on U.S. agriculture. As mentioned earlier, three transient GCMs are used in my impact study to project plausible future climate conditions in the United States. We describe these climate simulation models in the next chapter.

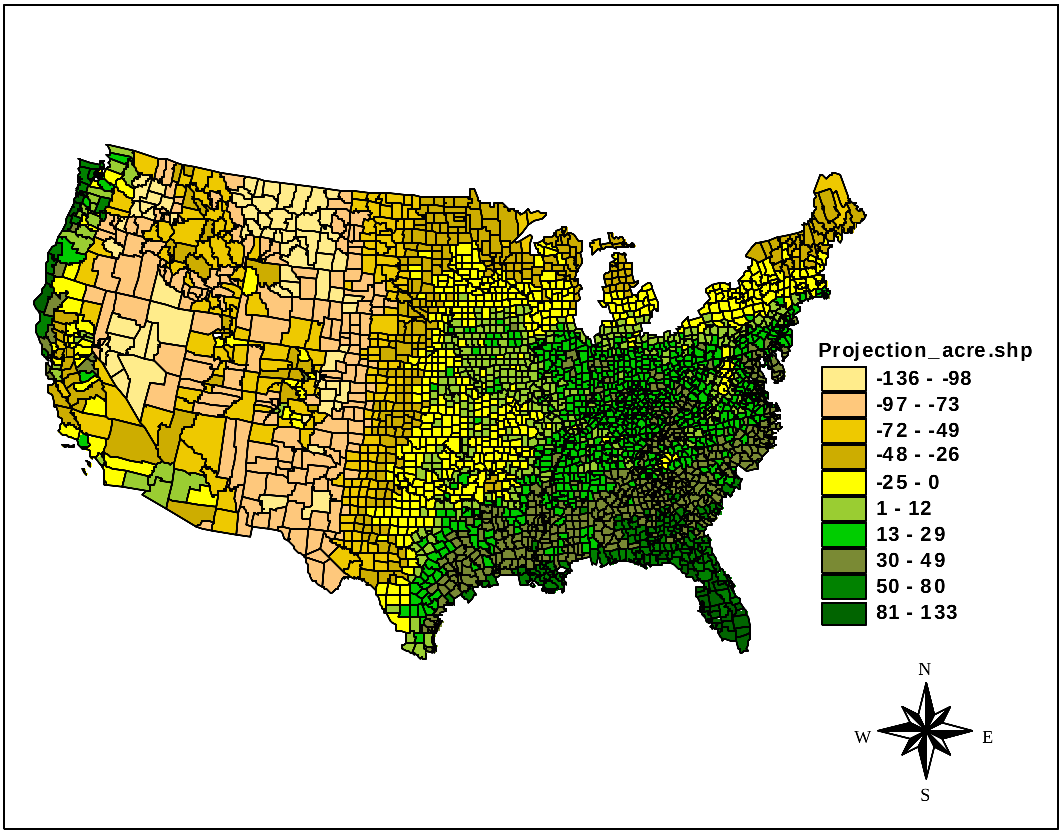
Table 6.3: Counties with the Most Valuable Climates per Acre of Farmland

County	State	Region	% Difference from the U.S. Sample Average
Tillamook	OR	Pacific	133%
Clatsop	OR	Pacific	129%
Dade	FL	Southeast	129%
Collier	FL	Southeast	125%
Lee	FL	Southeast	125%
Sarasota	FL	Southeast	118%
Broward	FL	Southeast	116%
Hendry	FL	Southeast	115%
Manatee	FL	Southeast	114%
Hernando	FL	Southeast	106%
Pasco	FL	Southeast	104%
Palm Beach	FL	Southeast	103%
Humboldt	CA	Pacific	103%
Hillsborough	FL	Southeast	101%
Charlotte	FL	Southeast	99%
Galdes	FL	Southeast	99%
Martin	FL	Southeast	94%
Okeechobee	FL	Southeast	94%
Levy	FL	Southeast	92%
Hardee	FL	Southeast	91%

Table 6.4: Counties with the Least Valuable Climates per Acre of Farmland

County	State	Region	% Difference from the U.S. Sample Average
Petroleum	MT	Mountain	-136%
Washakie	WY	Mountain	-131%
Chouteau	MT	Mountain	-131%
Cascade	MT	Mountain	-130%
Hill	MT	Mountain	-129%
Musselshell	MT	Mountain	-127%
Grant	WA	Pacific	-124%
Liberty	MT	Mountain	-124%
Treasure	MT	Mountain	-122%
Rosebud	MT	Mountain	-119%
Benton	WA	Pacific	-116%
Judith Basin	MT	Mountain	-116%
Teton	MT	Mountain	-116%
Garfield	MT	Mountain	-116%
Blaine	MT	Mountain	-115%
Custer	MT	Mountain	-115%
Toole	MT	Mountain	-114%
Fergus	MT	Mountain	-114%
Lyon	NV	Mountain	-113%
Lincoln	WA	Pacific	-113%

Figure 6.1: Relative Effects of Current Climate Conditions on U.S. Farmland Values per Acre (%)



Chapter 7: Climate Change Scenarios

Climate change scenarios are defined as plausible projections of human-induced future climate conditions that may be used to evaluate vulnerabilities of ecological or socio-economic systems. As concisely described by Rosenzweig and Hillel (1998), three types of climate change scenarios have been used in previous impact studies: arbitrary scenarios, historical analogs, and GCM-based scenarios.

1. Arbitrary Scenarios:

This first kind of scenario designates arbitrary changes of climate parameters such as a given rise in temperature or a given reduction in precipitation relative to observed baseline climate conditions. Projections with such arbitrary changes can be used to estimate the sensitivities of systems to given changes in climate variables. However, such scenarios do not provide comprehensive and consistent projections of climate variables (e.g., temperature, precipitation) as they are likely to change concurrently and interactively at both global and regional scales.

2. Historical Analogs:

In this methodology, historical climate extremes are used to construct analogous scenarios for climate change impact studies. To understand how societies might respond to future climate change, it would be informative to know how societies have been affected by and how they have coped with the effects of extreme meteorological events that have occurred in the recent past. This approach could provide insights on the responses of farmers and farming systems to periods of climate extremes. The notoriously hot and dry weather of the 1930s in the Southern Great Plains (The Dust Bowl) is probably the best-known example of an analogous scenario for future climate change. One of the problems associated with this kind of historical scenario approach is that the expected patterns of greenhouse gas-induced climate change may be quite different from the previous climate extremes. In addition, we have no observations for historical periods with climatic fluctuations as great as those predicted for the future global warming.

3. GCM-Based Scenarios:

General Circulation Models (GCMs) calculate the effects of all the key processes operating in the climate system in order to project how global and regional climates may changes in response to increased atmospheric concentrations of greenhouse gases. The most complex three-dimensional GCMs are called Atmospheric-Ocean General Circulation Models (AOGCMs). The AOGCMs that will be used in my impact studies solve the equations of the atmosphere and oceans approximately by breaking their domains up into volumetric grids, or boxes, each of which is assigned an average value for properties like temperature, velocity of wind, humidity (in the case of atmosphere) and salt (in the case of ocean). The size of the box is the model's spatial resolution; the smaller the box, the higher the resolution. The latest AOGCMs typically divide the atmosphere and ocean into a horizontal grid with a resolution of 2-4° latitude by 2-4° longitude, and 10 to 20 layers in the vertical. One of the nice features of the AOGCMs is that they can provide scenarios of transient (time-dependent) regional climate change as well as seasonal patterns of climatic change.

After an AOGCM is constructed, it can be simulated over prior years so that results can be compared to actual data. The AOGCMs' ability to reproduce a variety of observed features of the climate conditions and observed changes during the recent past supports their use for projections of future climate change. As pointed out in the IPCC Technical paper II, however, many uncertainties still remain regarding the modeling of the climate system (IPCC, 1997). To cope with these uncertainties, therefore, I use the following multiple climate change scenarios in my impact studies to project and compare the directions and relative magnitudes of potential future climate change in the continental United States. Table 7.1 summarizes some of the characteristics of these climate models.[18]

- **HadCM2** (Hadley Center Unified Model 2) based Scenario**:**

HadCM2 is the second version of the United Kingdom Hadley Center's GCM. This scenario simulates the change in radiative forcing of the climate system by greenhouse gases since the early industrial period (taken to be 1860). Thus HadCM2 is a 'warm-start' simulation. The model introduces scenario radiative forcing in 1990, and consists of a 1% per annum increase in equivalent

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[18] Source: MAGICC/SCENGEN developers, Mike Hulme, Tom Wiegly, and Olga Brown, January 2000.

CO_2 concentration through 2100. These simulations consist of four separate experiments with identical radiative forcing but with different initial conditions, a so-called "ensemble experiment." The global warming by 2071-2100, with respect to 1961-90, averaged 3.1° C in the four-member ensemble and the increase in global precipitation is 5.01%, yielding a global precipitation sensitivity of 1.6% per degree Celsius warming. The ensemble-mean response is used in my impact analysis.

- **CGCM1-TR** (the Canadian Global Coupled Model 1-Transient) based scenario**:**

CGCM1 is the first version of the Canadian Global Coupled Model. The experiment consists of a climate change simulation in which historical greenhouse gas forcing from 1860 to 1990 is followed by a 1% per annum increase in radiative forcing (CO_2 equivalent concentration) from 1990 to 2099. CGCM1-TR projects average-global warming by 2071-2100, relative to 1961-90, of 4.9° C. The increase in average-global precipitation is 5.54%, yielding a global precipitation sensitivity of 1.1% per degree Celsius warming.

- **ECHAM4** (European Center/Hamburg Model 4) based scenario**:**

This model is the current generation in the line of ECHAM models developed in Germany. Its simulations results that are used in my analysis are those from a climate change experiment in which historical greenhouse gas forcing from 1860 to 1990 is followed by a 1 % per annum increase in radiative forcing CO_2 equivalent concentration from 1990 to 2099. The global warming by 2071-2100, with respect to 1961-90, is 3.0°C and the increase in global precipitation is 1.97%, yielding a global precipitation sensitivity of 0.7% per degree Celsius warming.

Table 7.1: Summary Features of Selected GCMs

Model feature	HadCM2	CGCM1-TR	ECHAM4
Atmospheric resolution in horizontal (lat./long.)	2.5° by 3.75°	3.75° by 3.75°	2.8° by 2.8°
Atmospheric resolution in vertical	19 layers	10 layers	19 layers
Oceanic resolution in horizontal (lat./long.)	2.5° by 3.75°	1.8° by 1.8°	2.8° by 2.8°
Oceanic resolution in vertical	20 layers	29 layers	9 layers
Treatment of greenhouse gases	Equivalent CO_2	Equivalent CO_2	Equivalent CO_2
Global Warming by 2071-2100 with respect to 1961-90	3.1° C	4.9° C	3.0°C
Increase in global precipitation by 2071-2100 with respect to 1961-90	5.01%,	5.54%,	1.97%
Global precipitation sensitivity per °C warming	1.6%	1.1%	0.7%
Climate sensitivity to CO_2 doubling[19]	2.5°C (4.5°F)	3.5°C (6.3°F)	2.6°C (4.68°F)
Includes daily cycle?	Yes	Yes	Yes

These 3 AOGCMs are used in my research as representative climate change scenarios for several reasons. First, unlike the equilibrium-doubled CO_2 GCM scenarios used in the past, all of these models can generate transient climate

[19] The term *climate sensitivity* refers to the steady-state increase in the global annual mean surface temperature associated with a given global radiative forcing. It is common practice to use CO_2 doubling as a benchmark for comparing climate model sensitivities.

change scenarios, thus enabling me to examine time-evolving responses of the climate system as well as the seasonal patterns of the change at each county level in the contiguous U.S. Second, these models are developed to avoid the problem known as the 'cold-start problem' of the previous generation of transient GCMs. The cold-start problem made it difficult to assign calendar years to those previous GCM results. Third, HadCM2 and ECHAM4 both appear to reproduce observed climate conditions relatively well in the control simulation of the experiment. According to the report of the Climate Research Unit (CRU) at the University of East Anglia, UK, for example, HadCM2 and ECHAM4 all display fairly high levels of pattern correlation statistics among the 17 GCMs examined.[20] Although CGCM1-TR displays relatively low pattern correlation statistic, I also apply CGCM1-TR in my impact analysis in order to compare my results to NAST impact study, which uses CGCM1-TR and HadCM2 in its impact simulations.

I extract the climate change scenarios of HadCM2, CGCM1-TR, and ECHAM4 from the Model for the Assessment of Greenhouse-gas Induced Climate Change/SCENario GENerator (MAGICC/SCENGEN) developed at the CRU.[21] In fact, MAGICC/SCENGEN (version 2.4) was used to produce the global-mean temperature and sea-level rise projections given in the IPCC's 1995 Second Assessment Report (SAR). One of the nice features of MAGICC/SCEGEN is that it standardizes geographic and seasonal patterns of climate change scenario of each GCM to 1°C of global warming, enabling the user

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[20] The pattern correlation statistic mentioned here describes how well each GCM reproduces the observed global (land and ocean) pattern of mean monthly precipitation in the controlled simulation.

[21] I thank Dr. Mike Hulme at the CRU for generously providing me with MAGICC/SCENGEN.

to explore the consequences for future climate condition of adopting different assumptions about climate system parameters (e.g., climate sensitivity) and wide range of emissions scenarios.[22] Based on the IPCC's "IS92a" emissions scenario (Business-As-Usual scenario), I construct the projections of future climate changes in the U.S. as follows, using MAGICC/SCENGEN:

1. In order to analyze the time-dependent patterns of the effect of global warming on U.S. agriculture, I produce climate change scenarios from each GCM over the periods 2001-2030, 2031-2060, and 2061-2090. These 30-year interval projections include the relative changes of average temperature, daily (diurnal) range of temperature, and precipitation of each month with respect to the baseline period (i.e., 1961-1990).
2. Instead of imposing uniform changes in climate conditions across the contiguous United States, I derive the projected climate change fom each GCM at the county level so as to capture the geographical variations of the magnitude of climate changes across the continental U.S.[23]
3. The single largest source of uncertainty in projections of future climate change has been the equilibrium climate sensitivity, which is expected to fall between +1.5 to 4.5°C for CO_2 doubling. In order to take into account the uncertainty associated with the climate sensitivity, therefore, I

[22] For more technical details used by MAGICC/SCENGEN, refer to MAGICC/SCENGEN developers, Mike Hulme, Tom Wiegly, and Olga Brown, January 2000.
[23] Although the GCMs used in SCENGEN all operate at different spatial resolutions, the GCM data have all been interpolated to 5° latitude/longitude resolution for use in MAGICC/SCEGEN. I then matched the geographic center of each county with the 5° latitude/longitude resolution datasets in MAGICC/SCENGEN to obtain county-level climate change scenarios for each GCM.

calibrate each GCM under the assumptions of both low (1.5°C) and high (4.5°C) climate sensitivities, and apply the IPCC's "IS92a" emissions scenario (Business-As-Usual scenario) to each GCM to generate the plausible range of future climate conditions.

Therefore, the total number of climate change scenarios derived for use in my impact analysis thus consist of 216 greenhouse gas-induced future climate conditions in each county in the contiguous United States (3 GCMs $\times$ 3 time-intervals $\times$ 2 climate sensitivities $\times$ 3 climate variables $\times$ 4 seasons), as follows:

I. **Alternative assumptions, yielding six alternative cases.**
   A. Three GCMs:
      1. HadCM2
      2. CGCM1-TR
      3. EACHAM4
   B. Two climate sensitivities in response to CO_2 doubling.
      1. 1.5°C
      2. 4.5°C

II. **Each of six alternative cases requires 36 pieces of climate projections for these counties.**
   A. Three time-intervals:
      1. 2001-2030
      2. 2031-2060
      3. 2061-2090
   B. Three climate variables:
      1. Average temperature
      2. Daily temperature range
      3. Precipitation
   C. Four Seasons:
      1. Spring
      2. Summer
      3. Fall
      4. Winter

Table 7.2, 7.3, and 7.4 summarize the projections of future climate of each GCM extracted from MAGICC/SCENGEN. In addition, color maps in Appendix Figure B show some of the geographic and seasonal patterns of the projected climate change across the U.S. As are suggested by these tables and maps, the projected climate change is not likely to be uniform over the U.S., either geographically or seasonally.

Table7.2: HadCM2-Based Scenario[24]

Climate Sensitivity	Climate Variable	Season	2001-2030	2031-2060	2061-2090
1.5°C	Change in Temperature (Δ°C)	Spring	0.4 ~ 0.6	0.8 ~ 1.3	1.2 ~ 2.0
		Summer	0.4 ~ 0.6	0.9 ~ 1.4	1.3 ~ 2.1
		Fall	0.4 ~ 0.6	0.8 ~ 1.3	1.2 ~ 1.9
		Winter	0.3 ~ 0.7	0.6 ~ 1.5	0.8 ~ 2.3
	Change in Precipitation (Δ%)	Spring	-2.4 ~ 3.6	-5.2 ~ 7.8	-8.0 ~ 11.9
		Summer	-1.1 ~ 6.1	-2.4 ~ 13.1	-3.6 ~ 20.1
		Fall	1.8 ~ 13.6	3.8 ~ 29.5	5.9 ~ 45.3
		Winter	-5.7 ~ 12.4	-12.3 ~ 27.0	-18.9 ~ 41.3
	Change in Daily Temp. Range (Δ°C)	Spring	-0.1 ~ 0.1	-0.3 ~ 0.1	-0.4 ~ 0.2
		Summer	-0.2 ~ 0.0	-0.4 ~ 0.1	-0.7 ~ 0.0
		Fall	-0.3 ~ 0.0	-0.6 ~ -0.1	-0.9 ~ -0.1
		Winter	-0.3 ~ 0.2	-0.6 ~ 0.3	-0.9 ~ 0.5
4.5°C	Change in Temperature (Δ°C)	Spring	0.7 ~ 1.2	1.6 ~ 2.6	2.5 ~ 4.2
		Summer	0.8 ~ 1.2	1.8 ~ 2.8	2.8 ~ 4.4
		Fall	0.7 ~ 1.1	1.6 ~ 2.5	2.6 ~ 4.0
		Winter	0.5 ~ 1.4	1.1 ~ 3.1	1.8 ~ 4.9
	Change in Precipitation (Δ%)	Spring	-4.7 ~ 7.0	-10.5 ~ 15.7	-16.6 ~ 24.8
		Summer	-2.1 ~11.7	-4.8 ~ 26.4	-7.5 ~ 41.8
		Fall	3.4 ~ 26.4	7.8 ~ 59.5	12.3 ~ 94.2
		Winter	-11.0 ~ 24.1	-24.9 ~ 54.3	-39.4 ~ 86.0
	Change in Daily Temp. Range (Δ°C)	Spring	-0.2 ~ 0.1	-0.6 ~ 0.3	-0.9 ~ 0.4
		Summer	-0.4 ~ 0.0	-0.9 ~ 0.0	-1.4 ~ 0.0
		Fall	-0.6 ~ -0.1	-1.3 ~ -0.1	-2.0 ~ -0.2
		Winter	-0.5 ~ 0.3	-1.2 ~ 0.6	-1.9 ~ 1.0

[24] Figures in the tables (Table 7.2, 7.3, and 7.4) represent the range, across U.S. counties, of projected climate change relative to a baseline period (1961- 1990).

Table7.3: CGCM1-TR-Based Scenario

Climate Sensitivity	Climate Variable	Season	2001-2030	2031-2060	2061-2090
1.5°C	Change in Temperature (Δ°C)	Spring	0.3 ~ 0.7	0.6 ~ 1.5	1.0 ~ 2.3
		Summer	0.3 ~ 0.6	0.7 ~ 1.2	1.0 ~ 1.9
		Fall	0.3 ~ 0.6	0.7 ~ 1.4	1.1 ~ 2.1
		Winter	0.3 ~ 0.7	0.6 ~ 1.5	0.9 ~ 2.3
	Change in Precipitation (Δ%)	Spring	-1.9 ~ 35.1	-4.4 ~ 44.0	-6.8 ~ 67.5
		Summer	-4.0 ~ 5.2	-8.6 ~ 11.2	-13.2 ~ 17.1
		Fall	-1.5 ~ 8.1	-3.1 ~ 17.6	-4.8 ~ 27.0
		Winter	-1.9 ~ 35.1	-4.2 ~ 75.9	-6.4 ~ 116.4
	Change in Daily Temp. Range (Δ°C)	Spring	-0.3 ~ 0.1	-0.7 ~ 0.2	-1.1 ~ 0.3
		Summer	-0.1 ~ 0.2	-0.3 ~ 0.3	-0.4 ~ 0.5
		Fall	-0.1 ~ 0.2	-0.3 ~ 0.4	-0.4 ~ 0.6
		Winter	-0.4 ~ 0.3	-0.8 ~ 0.7	-1.3 ~ 1.1
4.5°C	Change in Temperature (Δ°C)	Spring	0.6 ~ 1.4	1.3 ~ 3.1	2.1 ~ 4.9
		Summer	0.6 ~ 1.1	1.4 ~ 2.5	2.2 ~ 3.9
		Fall	0.6 ~ 1.2	1.5 ~ 2.7	2.3 ~ 4.3
		Winter	0.5 ~ 1.4	1.2 ~ 3.1	1.9 ~ 4.9
	Change in Precipitation (%Δ)	Spring	-4.0 ~ 39.4	-8.9 ~ 88.7	-14.1 ~ 140.4
		Summer	-7.7 ~ 10.0	-17.4 ~ 22.5	-27.5 ~ 35.7
		Fall	-2.8 ~ 15.8	-6.3 ~ 35.6	-10.0 ~ 56.3
		Winter	-3.8 ~ 67.9	-8.5 ~ 153.1	-13.4 ~ 242.4
	Change in Daily Temp. Range (Δ°C)	Spring	-0.6 ~ 0.2	-1.4 ~ 0.4	-2.3 ~ 0.7
		Summer	-0.3 ~ 0.3	-0.6 ~ 0.6	-0.9 ~ 1.0
		Fall	-0.2 ~ 0.3	-0.5 ~ 0.7	-0.8 ~ 1.2
		Winter	-0.7 ~ 0.6	-1.7 ~ 1.4	-2.7 ~ 2.2

Table7.4: EACHAM4-Based Scenario

Climate Sensitivity	Climate Variable	Season	2001-2030	2031-2060	2061-2090
1.5°C	Change in Temperature (Δ°C)	Spring	0.3 ~ 0.8	0.6 ~ 1.6	0.9 ~ 2.5
		Summer	0.3 ~ 0.9	0.7 ~ 2.0	1.1 ~ 3.1
		Fall	0.4 ~ 0.8	0.8 ~ 1.8	1.2 ~ 2.8
		Winter	0.3 ~ 1.0	0.7 ~ 2.2	1.1 ~ 3.4
	Change in Precipitation (Δ%)	Spring	-4.7 ~ 2.3	-10.1 ~ 5.1	-15.4 ~ 7.8
		Summer	-6.3 ~ 2.6	-13.7 ~ 5.6	-21.1 ~ 8.6
		Fall	-4.4 ~ 2.5	-9.5 ~ 5.4	-14.5 ~ 8.3
		Winter	-4.0 ~ 5.4	-8.6 ~ 11.8	-13.1 ~ 18.1
	Change in Daily Temp. Range (Δ°C)	Spring	-0.1 ~ 0.0	-0.3 ~ 0.1	-0.4 ~ 0.1
		Summer	-0.1 ~ 0.1	-0.1 ~ 0.2	-0.2 ~ 0.2
		Fall	-0.1 ~ 0.0	-0.2 ~ 0.1	-0.2 ~ 0.1
		Winter	-0.4 ~ 0.0	-0.9 ~ 0.0	-1.4 ~ 0.0
4.5°C	Change in Temperature (Δ°C)	Spring	0.6 ~ 1.5	1.2 ~ 3.3	2.0 ~ 5.2
		Summer	0.6 ~ 1.8	1.5 ~ 4.1	2.3 ~ 6.5
		Fall	0.7 ~ 1.6	1.6 ~ 3.7	2.5 ~ 5.8
		Winter	0.6 ~ 2.0	1.4 ~ 4.4	2.3 ~ 7
	Change in Precipitation (Δ%)	Spring	-9.0 ~ 4.5	-20.3 ~ 10.2	-32.1 ~ 16.1
		Summer	-12.3 ~ 5.0	-27.7 ~ 11.2	-43.9 ~ 17.8
		Fall	-8.5 ~ 4.8	-19.1 ~ 10.9	-30.2 ~ 17.3
		Winter	-7.7 ~ 10.5	-17.3 ~ 23.8	-27.4 ~ 37.6
	Change in Daily Temp. Range (Δ°C)	Spring	-0.2 ~ 0.1	-0.5 ~ 0.1	-0.8 ~ 0.2
		Summer	-0.1 ~ 0.1	-0.3 ~ 0.3	-0.4 ~ 0.5
		Fall	-0.1 ~ 0.1	-0.3 ~ 0.1	-0.5 ~ 0.2
		Winter	-0.8 ~ 0.0	-1.9 ~ 0.0	-3 ~ 0.0

Chapter 8: Analysis of Climate Change Impacts

With the baseline regression in chapter 6 and climate change scenarios in chapter 7, we are now ready to examine the consequences of human-induced climate change for U.S. agriculture. We first consider the aggregate effect of global warming, and then move on to decompose the effect into the USDA farm production regions, quantifying how each region may be affected by changing climate as projected by each GCM.

AGGREGATE IMPACTS

Table 8.1 shows the results of eighteen different aggregate impact simulations (3 GCMs $\times$ 2 climate sensitivities $\times$ 3 time-intervals). In order to calculate the effect of changing climate on each county from each projection, I take each GCM's projected seasonal climate change (precipitation, average temperature, and daily temperature range) for each county and multiply it by the corresponding coefficients of each climate variable from the baseline regression, and multiply it by the average farm values of 1982, 1987, 1992 (measured in 1996 constant dollars) in each county, and then multiply it again by the average amount of total cropland of 1982, 1987, and 1992 in that county. Summing across all counties then produces aggregate impact projections shown in Table 8.1.

With surprising uniformity, all eighteen simulations suggest that the aggregate effects of global warming on the agricultural sector of the U.S. economy over the 21st century are slightly beneficial. In particular, aggregate impact projections based on EACHAM4 and HadCM2 are remarkably similar, while CGCM1-TR-based simulation predicts somewhat lower positive effects. In general, projections under the assumption of high climate sensitivity (4.5°C) predict positive effects that are 2-3 times greater than under the assumption of low climate sensitivity (1.5°C).

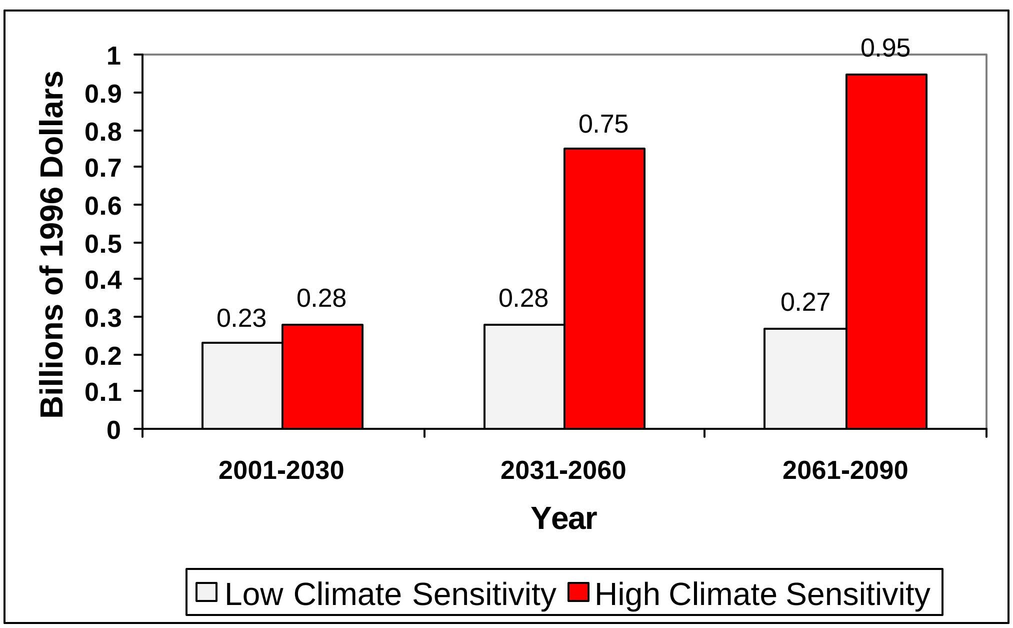
Table 8.1: Agricultural Impact Projections for the U.S. (1996 Billion Dollars)

GCM	Climate Sensitivity	2015	2045	2075
CGCM1-TR	*1.5°C*	0.23	0.28	0.27
	4.5°C	0.28	0.75	0.95
EACHAM4	*1.5°C*	2.05	4.19	6.47
	4.5°C	3.89	8.11	13.10
HadCM2	*1.5°C*	1.65	3.32	5.07
	4.5°C	2.71	6.41	10.24
Average		1.80	3.84	6.02

As noted in chapter 7, no single climate change scenario can be regarded as 'best.' If we assume, however, that all six climate change scenarios used in my impact study (3 GCMs × 2 climate sensitivities) have equal probability of occurring, then the expected beneficial effects of global warming on U.S. agriculture are reflected in land value increases of $1.8 billion in 2001-2030,

$3.84 billion in 2031-2060, and $6.02 billion in 2061-2090 time frame. Considering the fact that the total value of cropland in 1992 amounts to about $400 billion (in 1996 billion dollars) in the continental U.S., these projected impacts appear to be quite small (+0.45% ~ +1.51% in terms of the changes in the value of cropland). Figure 8.1, 8.2, and 8.3 graphically depict impact projections presented in Table 8.1. Of the three GCMs, the overall effect of global warming is projected to be least beneficial if the CGCM1-TR climate change scenario is realized, while US agriculture will benefit most if future climate conditions change as predicted by ECHAM4.

Figure 8.1: Land Value Impact Projections based on CGCM1-TR



<u>Figure 8.2: Land Value Impact Projections based on EACHAM4</u>

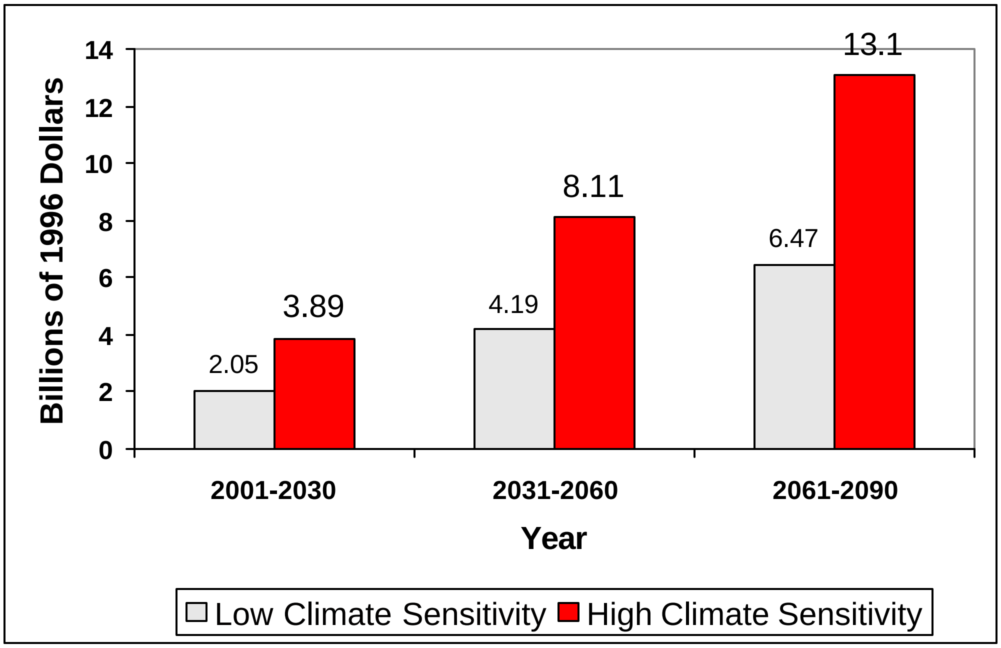
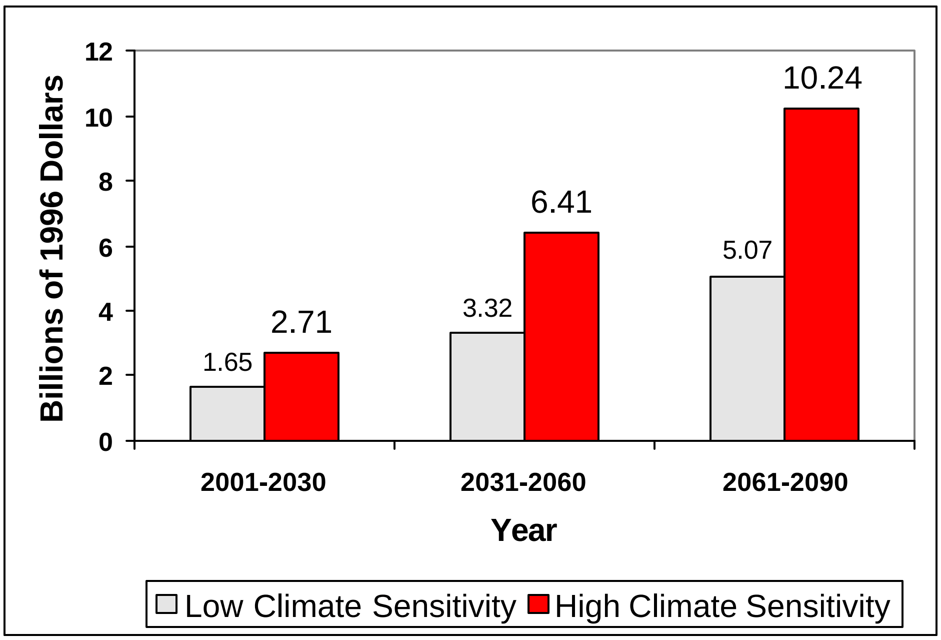


Figure 8.3: Land Value Impact Projections based on HadCM2



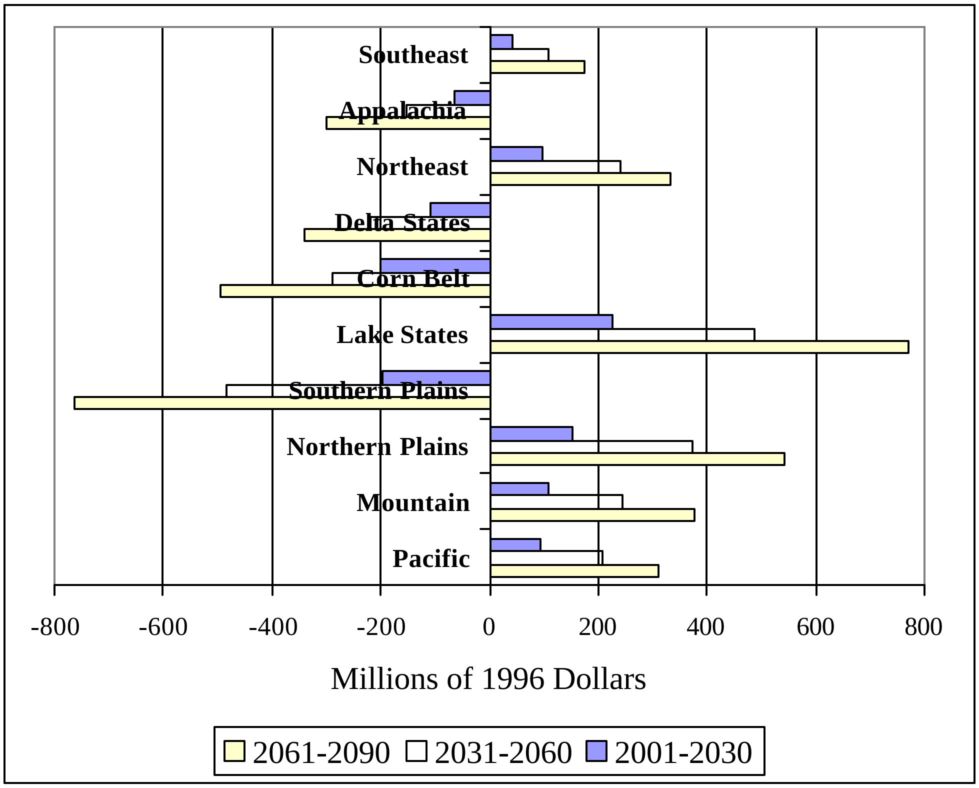
REGIONAL IMPACTS

While aggregate impact simulations suggest that climate change in the next 100 years is expected to be slightly beneficial for the US agricultural sector as a whole, the regional impacts are not likely to be uniform across the United States. For every GCM scenario considered in these simulations, the projected impacts vary region by region. Appendix Tables 1 through 10 summarize the results of 18 impact simulations (3GCMs $\times$ 2 climate sensitivity $\times$ 3 time-intervals) by USDA's 10 farm production regions. The regional impact projections are measured in 1996 millions of dollars.

Under the CGCM1-TR climate change scenario, winners for all three time-intervals include the Lake States, the Northern Plains, the Northeast Region, the Mountain Region, the Pacific Region, and the Southeast Region. In contrast, those expected to suffer losses include the Southern Plains, the Corn Belt, Delta States, and the Appalachian Region. In this simulation, the Lake States benefit most, and the Southern Plains are projected to be the biggest loser.

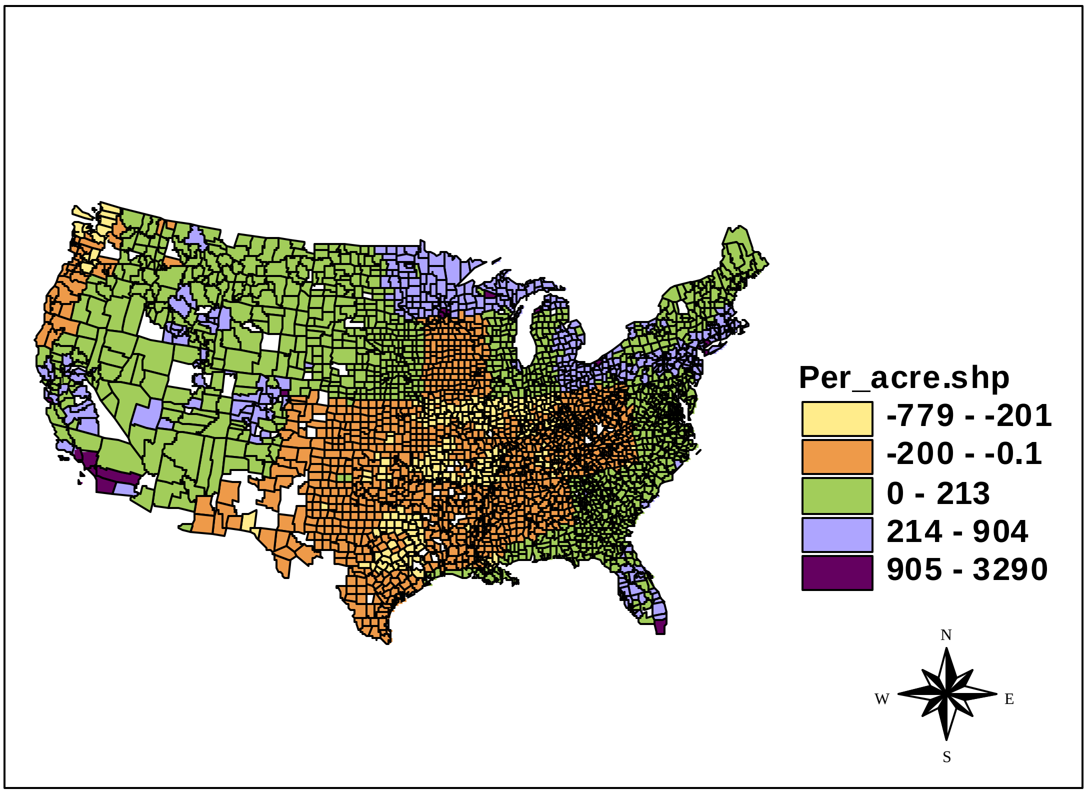
Figure 8.4 depicts the regional effects of climate change under the CGCM1-TR scenario. The projection in Figure 8.4 is obtained by averaging the results of impact simulations based on the assumptions of low climate sensitivity and high climate sensitivity, and then adding together all the counties within each region.

Figure 8.4: CGCM1-TR-based Regional Impact Projection



Using a color map, Figure 8.5 also shows the projected effect of climate change per acre of cropland, in the 2031-2060 time interval for the continental U.S., under the CGCM1-TR scenario, assuming high climate sensitivity.

Figure 8.5: Change in Value of Cropland, in $/acre in Each County, using CGCM1-TR-based Scenario (2031-2060, High Climate Sensitivity)



The ECHAM4-scenario-based impact simulation, however, produces a rosier prediction. According to this projection, the effect of global warming is expected to be positive for all regions and all time intervals (2001-2030, 2031-2060, and 2061-2090).

Among the regions, the Corn Belt is expected to be the biggest winner, followed by the Northern Plains, the Lake States, and the Northeast Region as shown in Figure 8.6. Again, The impact projection in Figure 8.6 represents the average of simulation results under the assumptions of low climate sensitivity and high climate sensitivity. Figure 8.7 presents more detailed spatial distribution of the effect of climate change (change in value of cropland per acre) in 2031-2060 time interval for the continental U.S. under ECHAM4 scenario, assuming high climate sensitivity.

Figure 8.6: ECHAM4-based Regional Impact Projection

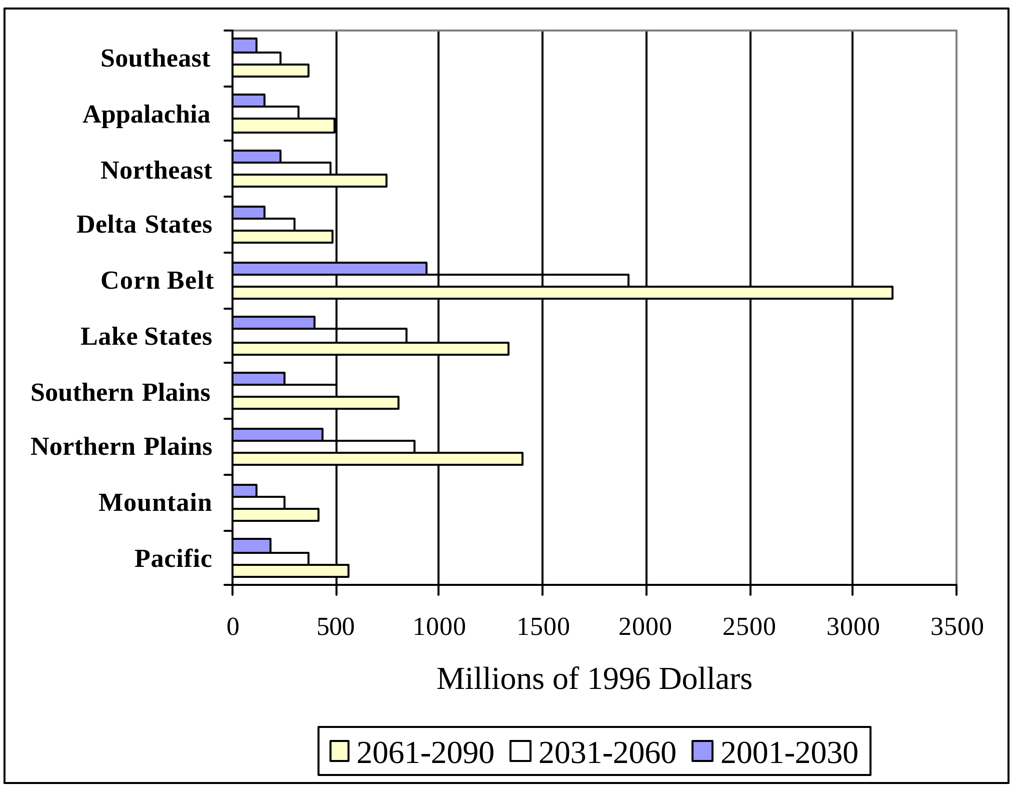
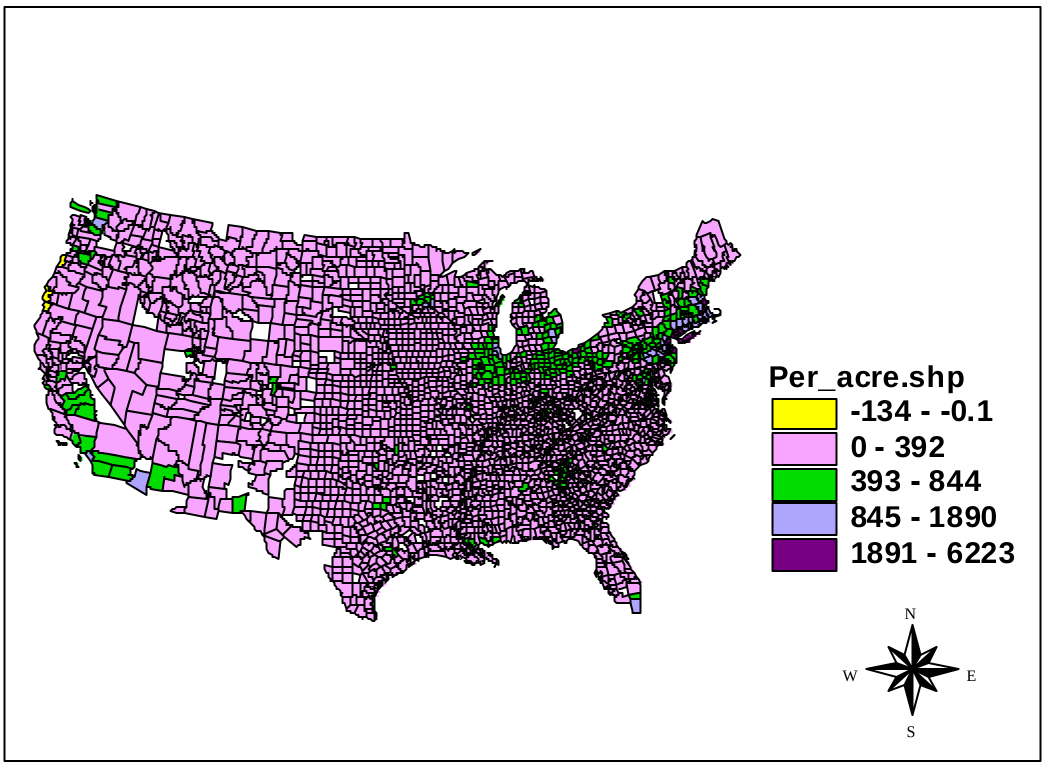


Figure 8.7: Change in Value of Cropland, in $/acre in Each County, using ECHAM4-based Scenario (2031-2060, High Climate Sensitivity)



As shown in Figure 8.8, HadCM2-based simulation also projects a beneficial effect of global warming for U.S. agriculture for all regions but the Southern Plains. As in the ECHAM4 based projection, the Corn Belt is found to benefit most from changing climate. Compared with other regions, the beneficial effects are relatively high for the Northern Plains, the Pacific Region, and the Lake States. Though positive, the effects are projected to be very small for the Southeast Region, the Delta States, and the Northeast Region as shown in Figure 8.8.

Figure 8.8: HadCM2-based Regional Impact Projection

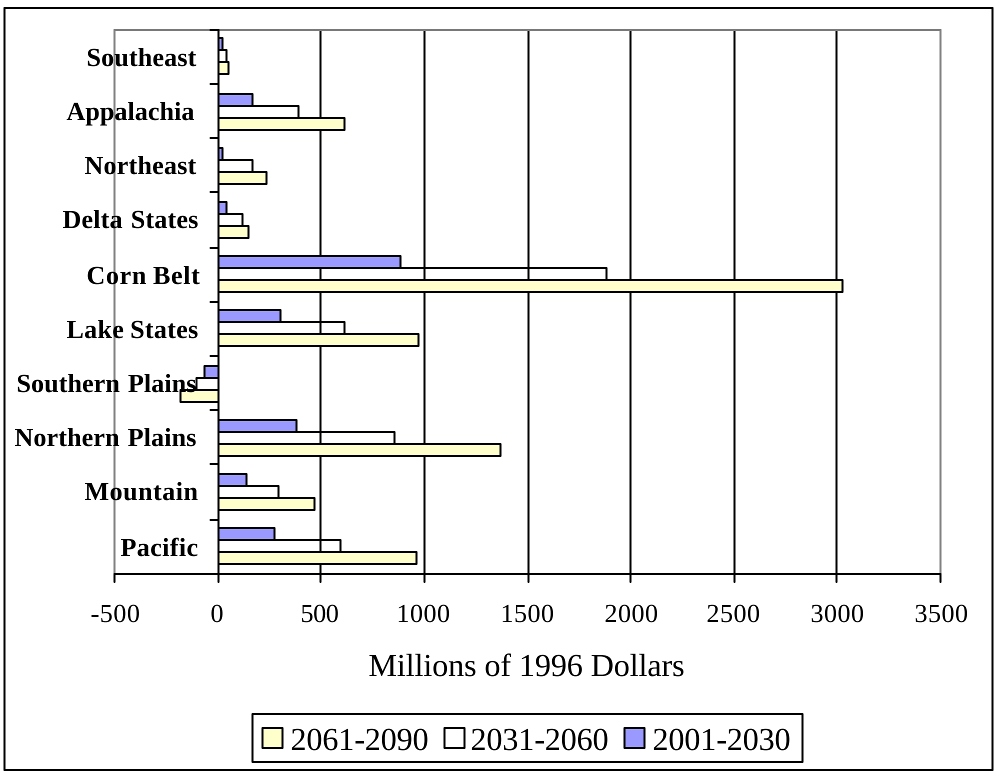
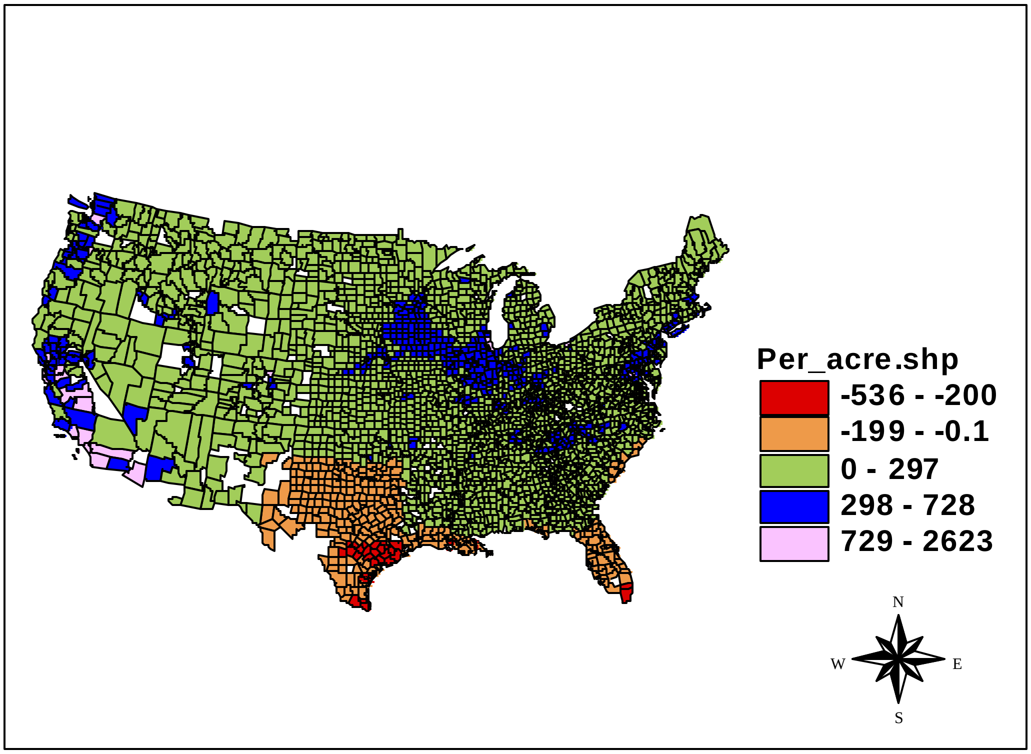


Figure 8.9: Change in Value of Cropland, in $/acre in Each County, using HadCM2-based Scenario (2031-2060, High Climate Sensitivity)



As we have seen so far, regional impact projections differ in a way that depends on the choice of general circulation model (GCM). In particular, the CGCM1-TR-based simulation produces significantly different regional impact projections compared with other projections based on EACHM4 and HadCM2 scenarios. Regardless of which GCM is used in simulations, however, six out of ten USDA farm production regions are consistently expected to benefit from greenhouse gas-induced climate change over the next 100 years. Those regions include the Lake States, the Northern Plains, the Pacific Regions, the Northeast Region, the Mountain Region, and the Southeast Region.

Now, what drive these differences in impact projections between the three GCMs? Obviously, these differences in impact projections are the results of the differences in simultaneous interactions between each GCM's projected seasonal climate change (precipitation, average temperature, and daily temperature range) for each county and the corresponding coefficients of each climate variable from the baseline regression (i.e., twelve coefficients). Since the impact projections between the three climate models show significant differences for the Corn Belt, the Appalachian Region, the Delta States, and the Southern Plains (especially under the CGCM1-TR-based scenario), I select the counties in these regions that display noticeable disagreements in impact projections, and run separate impact simulations for each of 12 climate variables (3 climate variables $\times$ 4 seasons) for these regions to analyze the differences between the GCMs that drive the differences in impact projections. The results are summarized in Table 8.2 (Corn Belt), 8.3 (Appalachian Region), 8.4 (Delta States), and 8.5 (South Plains).

Table 8.2: Impact Projections for Counties in the Corn Belt that show Losses under the CGCM1-TR-based Scenario (2031-2060, High Climate Sensitivity)

Climate Variable	*Sign of Estimated Coefficient*	CGCM1-TR		EACHM4		HadCM2	
		Projected Change in Climate Variable	*Impact Projection ($1996 million)*	*Projected Change in Climate Variable*	*Impact Projection ($1996 million)*	*Projected Change in Climate Variable*	*Impact Projection ($1996 million)*
Spring Precipitation	+	6.48%	333	3.86%	185	14.65%	712
Summer Precipitation	-	-4.29%	78	6.21%	-151	7.49%	-190
Fall Precipitation	-	5.34%	-97	7.19%	-119	15.49%	-263
Winter Precipitation	-	5.37%	-4	3.41%	-3	15.76%	-14
Spring Temperature	-	2.10°C	-1,800	2.64°C	-2,270	1.75°C	-1,453
Summer Temperature	-	1.92°C	-75	3.00°C	-122	1.94°C	-76
Fall Temperature	+	2.41°C	3,515	3.23°C	4,867	2.02°C	3,048
Winter Temperature	-	2.12°C	-1,147	2.71°C	-1,512	1.98°C	-1,112
Spring Daily Temperature Range	+	-0.15°C	-157	-0.29°C	-405	-0.42°C	-606
Summer Daily Temperature Range	-	-0.27°C	531	-0.10°C	157	-0.30°C	471
Fall Daily Temperature Range	+	-0.11°C	-159	-0.26°C	-330	-0.59°C	-791
Winter Daily Temperature Range	-	0.99°C	-1,819	-0.39°C	898	-0.85°C	1,818
Aggregate Impact Projection			-801		1,195		1,544

An examination of Table 8.2 reveals that, under the CGCM1-TR-based climate change scenario, the determining climate variables that lead to the negative overall impact projection for the Corn Belt are spring temperature, winter temperature, and winter daily temperature range. In particular, the CGCM1-TR scenario displays a significant increase of winter daily temperature

(+0.99°C) range, whereas both EACHM4 and HadCM2 scenarios predict a decrease of winter temperature range (-0.39°C and -0.85°C, respectively), resulting in big a difference in impact projections between the CGCM1-TR and the other two climate models. For all four seasons, the EACHM4 and HadCM2 scenarios predict more rainfall, more warming, and drops in daily temperature ranges. On the other hand, the CGCM1-TR predicts a decrease of precipitation in summer. In addition, under the EACHM4 scenario, fall temperature is expected to rise as much as 3.23°C, generating highly beneficial effect on the value of cropland in this region.

A similar pattern occurs for the Appalachian Region, as shown in Table 8.3. Spring temperature, winter temperature, and winter daily temperature range are expected to have harmful effects for the Appalachian Region under the CGCM1-TR scenario, outweighing the highly beneficial effect of fall temperature on farm values. As is the case in the Corn Belt, EACHM4 and HadCM2 scenarios for the Appalachian Region exhibit good agreements between them in terms of the signs for the climate variables (more rainfall, more warming, and drops in daily temperature range in all seasons). On the other hand, the CGCM1-TR displays drops in summer and fall rainfall, and increases of three seasons' daily temperature ranges: the increases in summer and fall daily temperature range appear to be relatively minor, but the positive change in winter daily temperature range (+1.08°C) causes a significant difference in impact projection.

Table 8.3: Impact Projections for Counties in the Appalachian Region that Show Losses under the CGCM1-TR-based Scenario (2031-2060, High Climate Sensitivity)

Climate Variable	*Sign of Estimated Coefficient*	**CGCM1-TR**		**EACHM4**		**HadCM2**	
		Projected Change in Climate Variable	*Impact Projection ($1996 million)*	*Projected Change in Climate Variable*	*Impact Projection ($1996 million)*	*Projected Change in Climate Variable*	*Impact Projection ($1996 million)*
Spring Precipitation	+	3.42%	69	4.14%	77	14.29%	248
Summer Precipitation	-	-8.25%	55	9.92%	-69	7.17%	-53
Fall Precipitation	-	-0.61%	-1	4.09%	-25	14.07%	-71
Winter Precipitation	-	1.77%	-1	5.23%	-3	17.48%	-9
Spring Temperature	-	1.84°C	-432	2.44°C	-571	1.86°C	-430
Summer Temperature	-	2.06°C	-23	2.70°C	-30	2.00°C	-22
Fall Temperature	+	2.50°C	1,035	2.94°C	1,223	1.90°C	787
Winter Temperature	-	2.04°C	-307	2.50°C	-374	1.80°C	-269
Spring Daily Temperature Range	+	-0.08°C	-42	-0.24°C	-98	-0.34°C	-137
Summer Daily Temperature Range	-	0.14°C	-37	-0.10°C	44	-0.30°C	132
Fall Daily Temperature Range	+	0.24°C	69	-0.24°C	-95	-0.54°C	-206
Winter Daily Temperature Range	-	1.08°C	-636	-0.30°C	172	-0.74°C	433
Aggregate Impact Projection			-251		251		403

As shown in Table 8.4, for the Delta States, we again notice good agreements between EACHM4 and HadCM2 scenarios and less agreement between the CGCM1-TR and the other two GCMs in terms of the signs for the climate variables. Not surprisingly, one of the main reasons for the difference in impact projection between the CGCM1-TR and the other two models is a projected rise in winter daily temperature range (+0.48°C) under the CGM1-TR scenario, among other things.

Table 8.4: Impact Projections for Counties in the Delta States that show Losses under the CGCM1-TR-based Scenario (2031-2060, High Climate Sensitivity)

Climate Variable	*Sign of Estimated Coefficient*	**CGCM1-TR** *Projected Change in Climate Variable*	**CGCM1-TR** *Impact Projection ($1996 million)*	**EACHM4** *Projected Change in Climate Variable*	**EACHM4** *Impact Projection ($1996 million)*	**HadCM2** *Projected Change in Climate Variable*	**HadCM2** *Impact Projection ($1996 million)*
Spring Precipitation	+	-2.52%	-31	2.72%	44	9.47%	178
Summer Precipitation	-	-10.63%	64	4.19%	-25	8.66%	-58
Fall Precipitation	-	6.48%	-39	5.26%	-32	18.18%	-93
Winter Precipitation	-	-1.23%	0.45	2.31%	-1	3.60%	-2
Spring Temperature	-	1.97°C	-448	2.31°C	-524	1.78°C	-397
Summer Temperature	-	2.13°C	-22	2.56°C	-28	2.06°C	-22
Fall Temperature	+	2.61°C	1,027	3.01°C	1,216	1.84°C	737
Winter Temperature	-	2.11°C	-308	2.17°C	-317	1.59°C	-235
Spring Daily Temperature Range	+	-0.25°C	-103	-0.22°C	-84	-0.20°C	-74
Summer Daily Temperature Range	-	0.21°C	-46	-0.12°C	47	-0.30°C	126
Fall Daily Temperature Range	+	-0.21°C	-92	-0.30°C	-107	-0.60°C	-215
Winter Daily Temperature Range	-	0.48°C	-312	-0.36°C	200	-0.33°C	204
Aggregate Impact Projection			-310		389		149

Table 8.5: Impact Projections for Counties in the South Plains that show Losses under the CGCM1-TR-based Scenario (2031-2060, High Climate Sensitivity)

Climate Variable	*Sign of Estimated Coefficient*	**CGCM1-TR**		**EACHM4**		**HadCM2**	
		Projected Change in Climate Variable	*Impact Projection ($1996 million)*	*Projected Change in Climate Variable*	*Impact Projection ($1996 million)*	*Projected Change in Climate Variable*	*Impact Projection ($1996 million)*
Spring Precipitation	+	-3.31%	-61	-2.52%	-34	3.68%	78
Summer Precipitation	-	-7.33%	59	-2.74%	18	7.96%	-60
Fall Precipitation	-	4.56%	-41	1.27%	-13	15.82%	-125
Winter Precipitation	-	2.70%	-0.2	-2.40%	0.9	-5.02%	3
Spring Temperature	-	2.18°C	-810	2.57°C	-957	2.04°C	-763
Summer Temperature	-	2.14°C	-38	2.93°C	-52	2.23°C	-40
Fall Temperature	+	2.50°C	1,646	3.20°C	2,108	1.98°C	1,312
Winter Temperature	-	2.31°C	-553	2.29°C	-550	1.99°C	-477
Spring Daily Temperature Range	+	-0.09°C	-55	-0.05°C	-28	-0.04°C	-19
Summer Daily Temperature Range	-	0.10°C	-64	-0.12°C	92	-0.32°C	222
Fall Daily Temperature Range	+	-0.15°C	-103	-0.25°C	-153	-0.68°C	-399
Winter Daily Temperature Range	-	0.71°C	-632	-0.26°C	233	-0.18°C	140
Aggregate Impact Projection			-652		665		-128

For the South Plains (Table 8.5), only the EACHM4-based simulation produces a positive impact projection. Higher expected change in fall temperature (3.20°C) relative to those of CGCM1-TR and HadCM2 (2.50°C and 1.98°C, respectively) appears to be the determining factor contributing to its beneficial impact projection of global warming on farm values in this region. A rise of winter daily temperature range under the CGCM1-TR is also a significant factor explaining the harmful impact projection of the Canadian climate model for this region. As for the HadCM2's negative impact projection, it has a lower beneficial effect of warming associated with its smaller rise in fall temperature (1.98°C), compared to the other models, and this smaller beneficial effect is therefore outweighed by the harmful effect of other climate variables.

Thus far, I've tracked down the reasons for the differences in results between the three climate models. The point of the calculations shown in Table 8.2, 8.3, 8.4, and 8.5 is to find out which portion of the climate projections differs across the three models in a way that drives the biggest difference in economic results. A certain area has a loss using one model and a gain using another model. Those who make such models might want to know which of the differences in their models are actually important, in terms of economic implications. They might see differences in temperature, or precipitation, or temperature range, but not know how much any of it matters. In other words, it is not enough to see which climate projection is the most different across the three models, because that season's temperature or precipitation variable may have a low estimated coefficient and therefore low impact on results. One also needs a hedonic model like this one (Chapter 4, 5, and 6) to know how those variables impact the economy to determine which differences in climate projections are having the biggest impacts on land values. That information can then be used by those who design general circulation models to know where to concentrate their efforts. As it turns out, the economic differences are driven in large part by different projections for winter daily temperature range, and a few other variables, so those are the projections of a GCM that might be most important to refine.

Chapter 9: Concluding Remarks

According to studies reported on the New York Times (Monday, February 19, 2001), the seemingly perpetual icecap atop Mount Kilimanjaro is retreating at such a pace that it is likely to disappear in less than 15 years. To some researchers, the vanishing of the snows of Kilimanjaro, which once inspired Ernest Hemingway, along with similar trends on ice-capped peaks from Peru to Tibet, is convincing evidence that global warming is not just coming; it's already here.

My dissertation takes on the issue of the likely impacts of global climate change on U.S. agriculture, and finds that the U.S. agricultural sector is resilient enough to cope with anthropogenic-induced climate change, at least over the next 100 years. More specifically, U.S. agriculture is expected to benefit marginally (in 1996 dollars) about $1.8 billion during 2001-2030, $3.84 billion during 2031-2060, and $6.02 billion during 2061-2090 time periods. Some regional impacts, however, may be disruptive, especially if future climate changes as projected by the Canadian model (CGCM1-TR), in which the Southern Plains (Texas, Oklahoma) is the most vulnerable region.

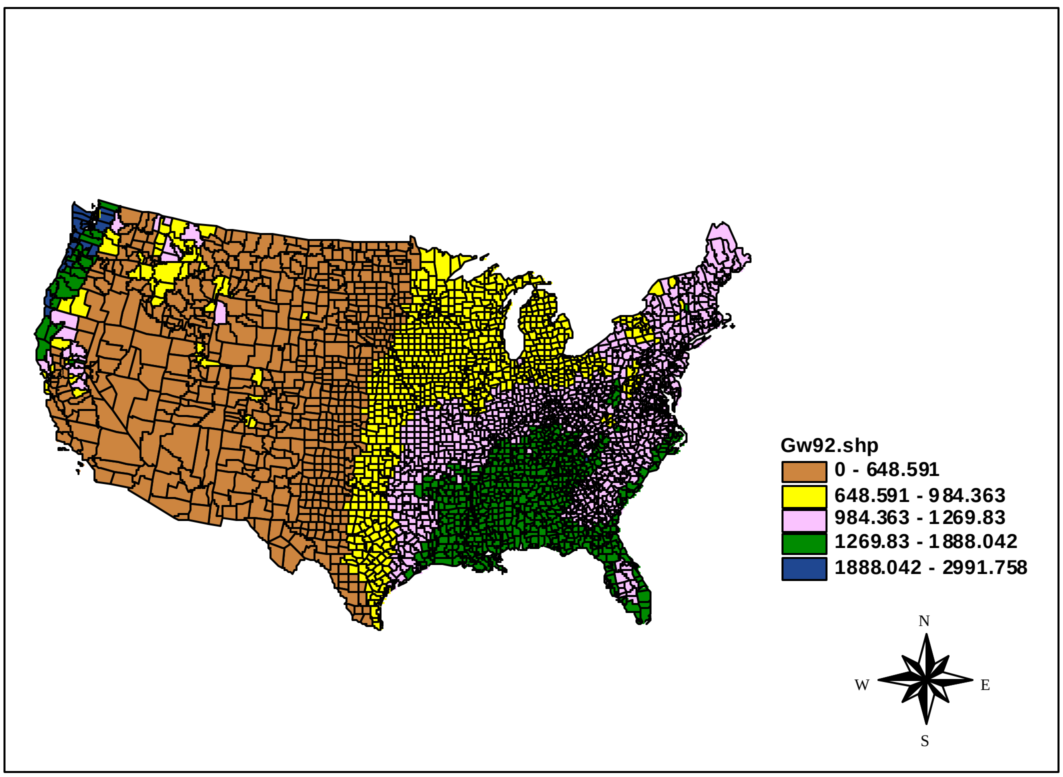
Interestingly, my agricultural impact projections, although not completely comparable to each other, appear quite similar to the work of Agricultural Sector Assessment Team of the NAST described in the Literature Review (Chapter 3). For example, the NAST's study also finds that, under the HadCM2 scenario, the projected agricultural impacts are positive for all regions in both 2030 and 2090 time frames. They also predict that, under the Canadian scenario, the opposing regional economic effects are nearly balanced, resulting in a small net beneficial effect on U.S. agriculture; the effect is positive for most northern regions, mixed for the northern Plains, and negative for Appalachia, the Southeast, the Delta States, and the southern Plains. As discussed in the Literature Review above, the NAST's agricultural impact study is primarily based on a crop simulation model approach, and the close agreements between the NAST's research and my impact projections may indicate that the two methodologies (Ricardian approach and crop simulation model approach) complement each other; the Ricardian approach facilitates the examinations of the distributional (regional) consequences of global warming across the nation, while the crop simulation model approach provides more integrated picture of climate change, crop-yields, and economic responses.

Global warming is a unique challenge. One must weigh the likely costs of slowing down warming, which are incurred today, against the likely benefits of slowed warming that will occur in the future. In addition, one must also address issues arising from the divergence between domestic costs of warming and global costs of warming. In other words, we're confronting negative externalities at a global scale; it doesn't matter where the emissions of greenhouse gases occur. Greenhouse gases mix completely in the atmosphere within a couple of years after emitted. Continuing efforts to evaluate and mitigate the likely consequences of global warming are badly needed to tackle perhaps one of the most pressing environmental problems mankind has ever faced.

Appendices

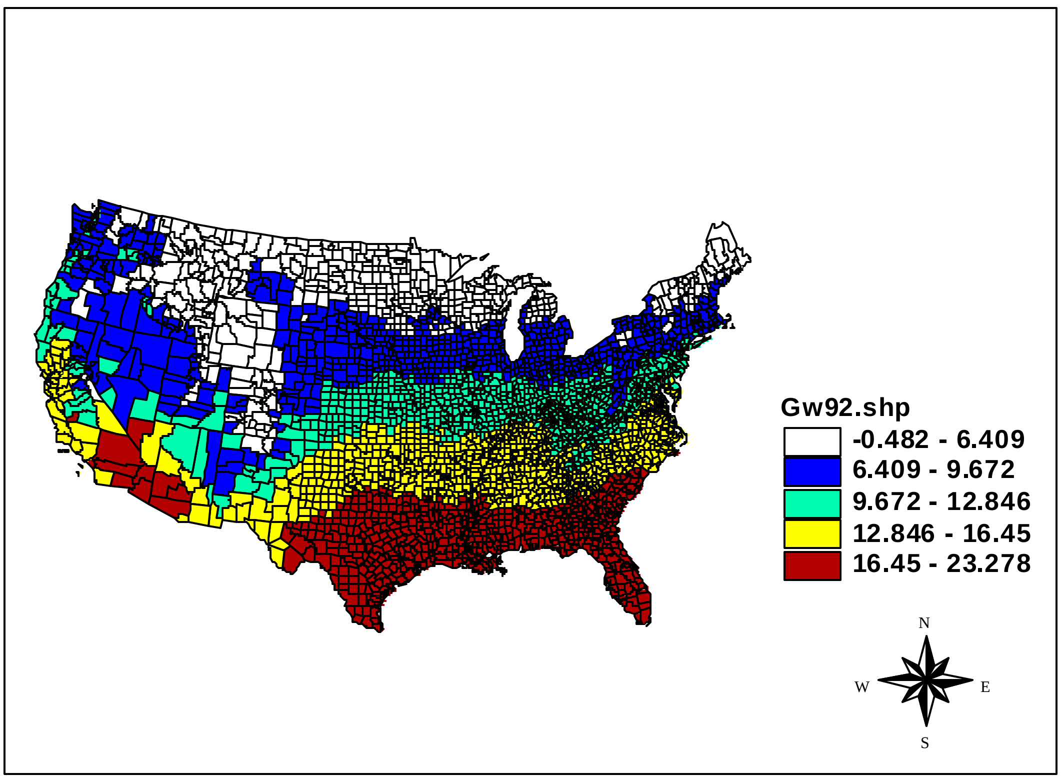
APPENDIX FIGURE A

Appendix Figure A-1: U.S. Annual Precipitation (1961-1990, mm)



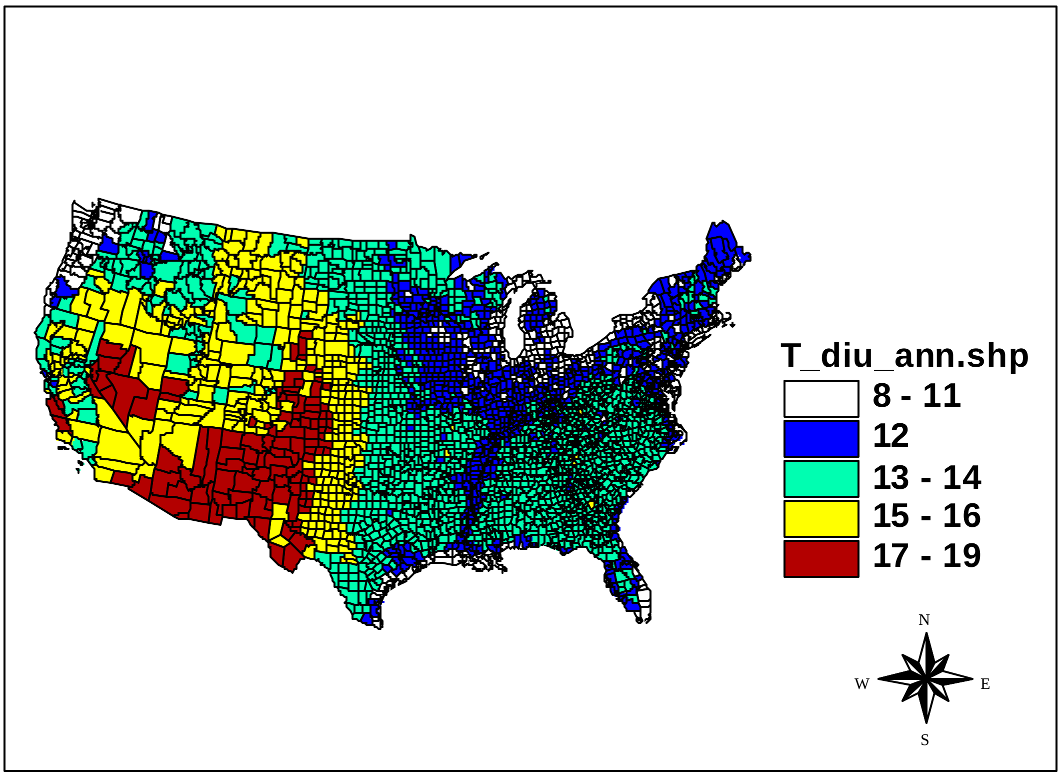
Source: NRCS, USDA & SCAS, OSU

Appendix Figure A-2: U.S. Average Annual Temperature (1961-1990, °C)



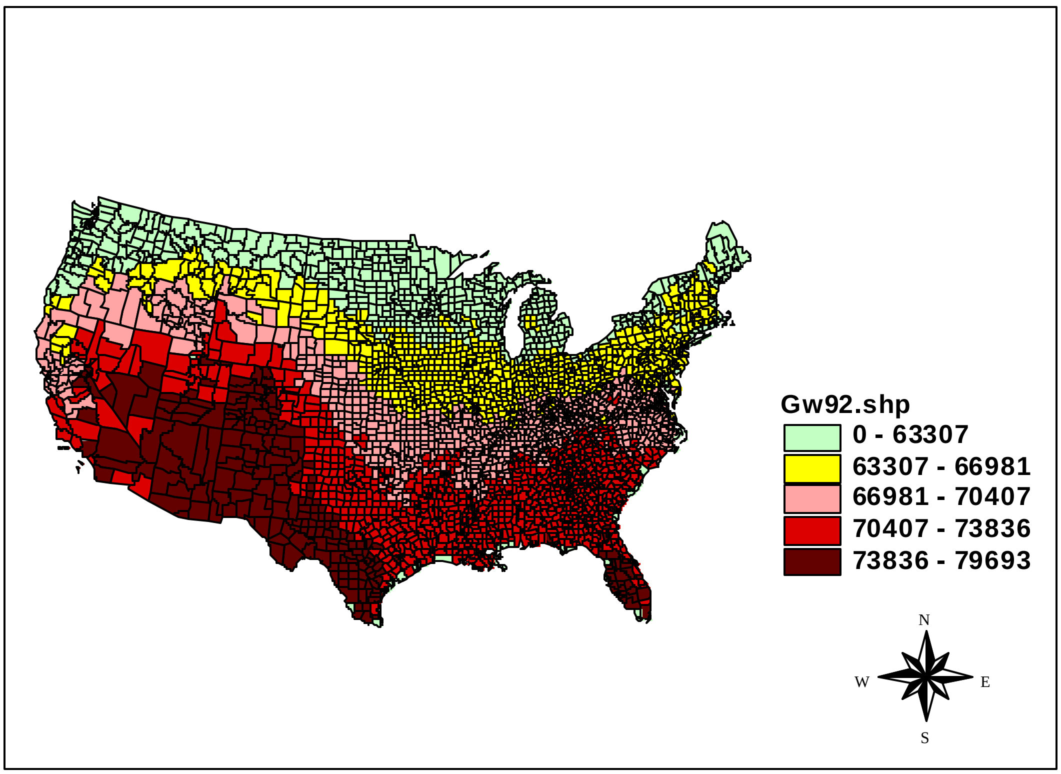
Source: NRCS, USDA & SCAS, OSU

Appendix Figure A-3: U.S. Annual Daily Temperature Range (1961-1990)



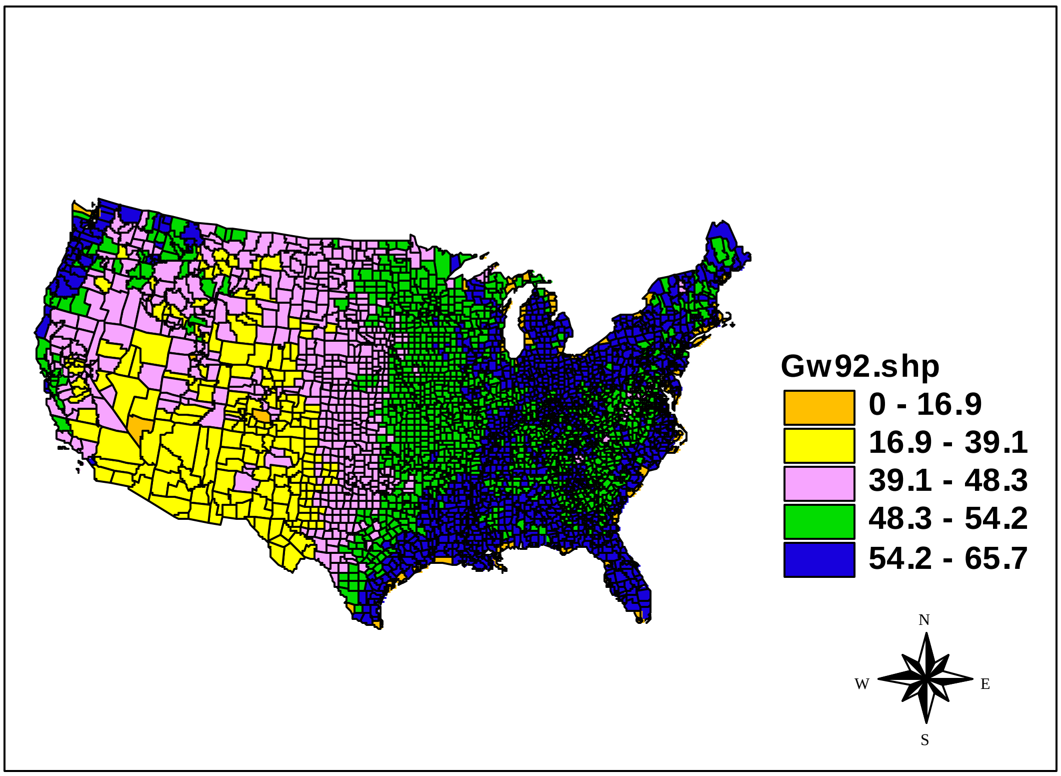
Source: NRCS, USDA & SCAS, OSU

Appendix Figure A-4: U.S. Annual Solar Radiation (1895-1993)



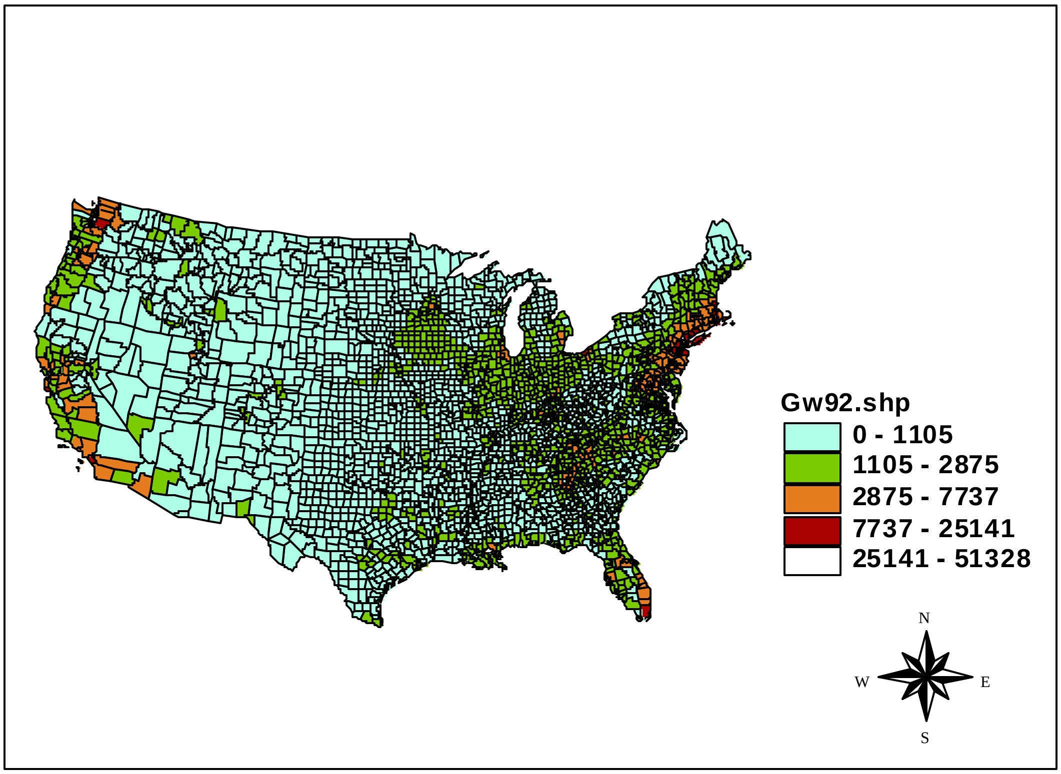
Source: VEMAP

Appendix Figure A-5: U.S. Annual Relative Humidity (1895-1993)



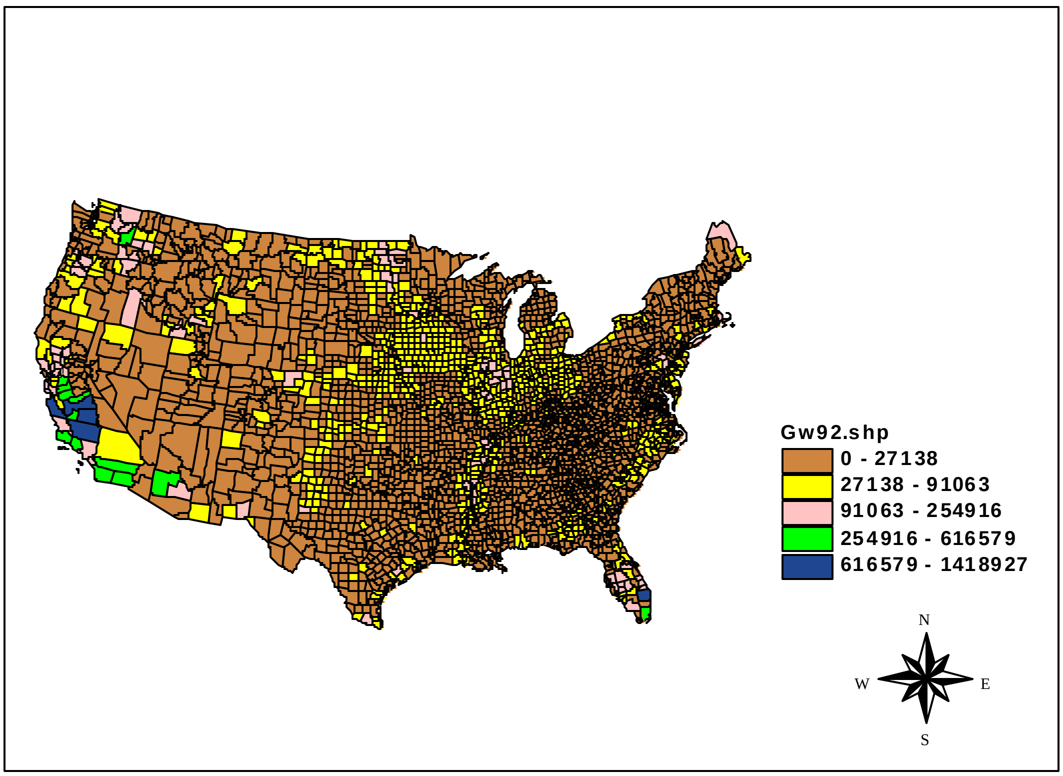
Source: VEMAP

Appendix Figure A-6: U.S. Value of Farmland per Acre in Dollars (Year 1992)



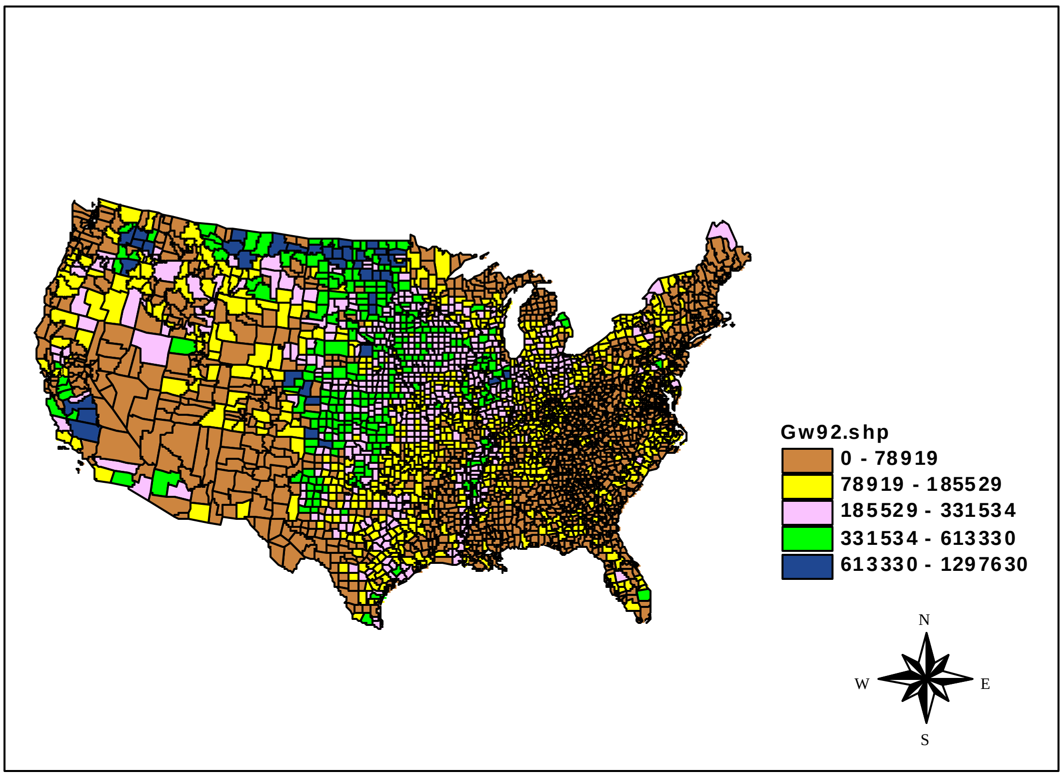
Source: USA Counties 1998 CD-ROM

Appendix Figure A-7: U.S. Total Value of Crop Revenue in Dollars (Year 1992)



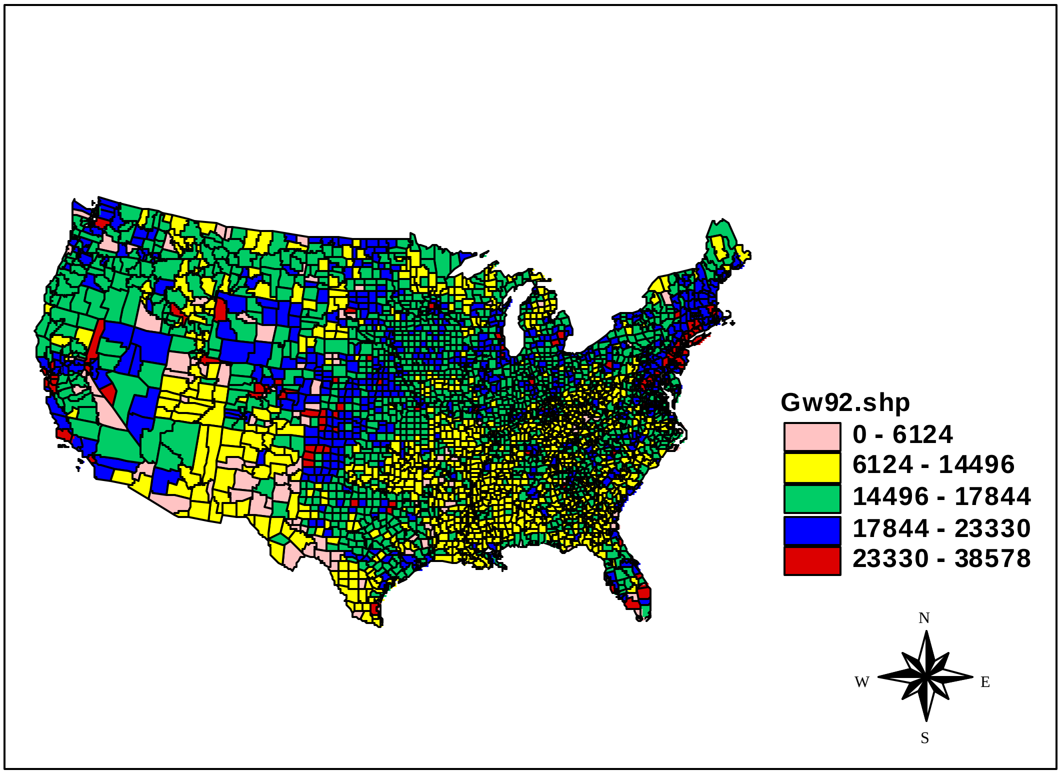
Source: USA Counties 1998 CD-ROM

Appendix Figure A-8: U.S. Total Cropland in Acres
(Year 1992)



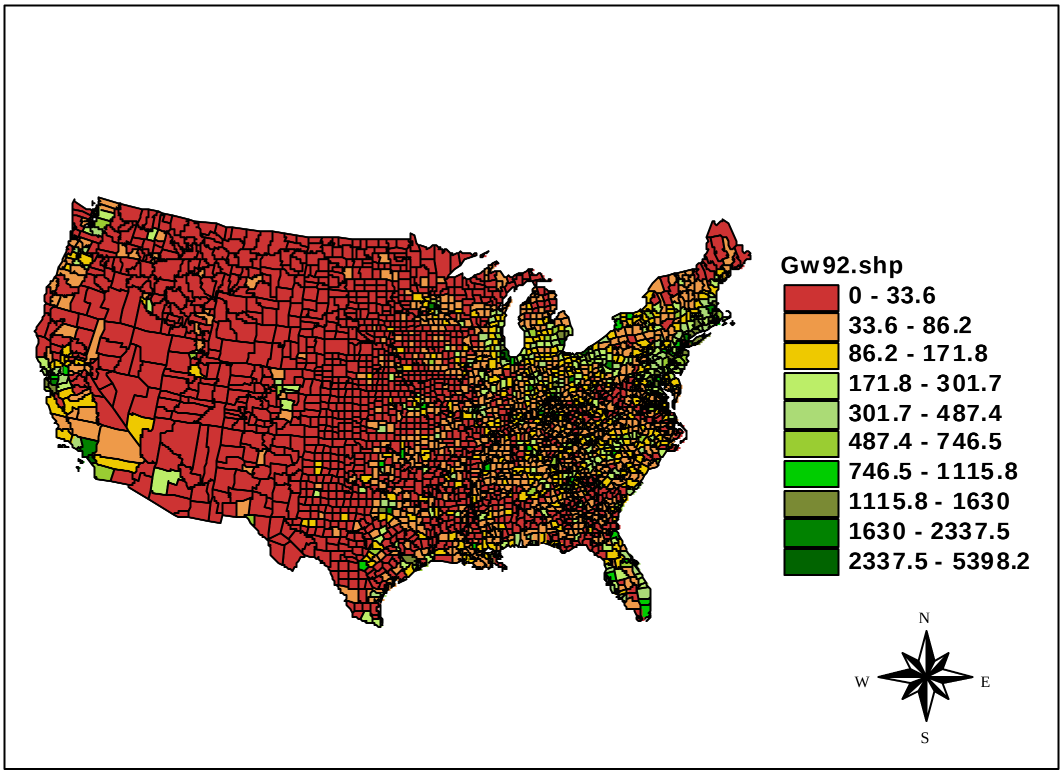
Source: USA Counties 1998 CD-ROM

Appendix Figure A-9: U.S. Per Capita Annual Personal Income In Dollars (Year 1992)



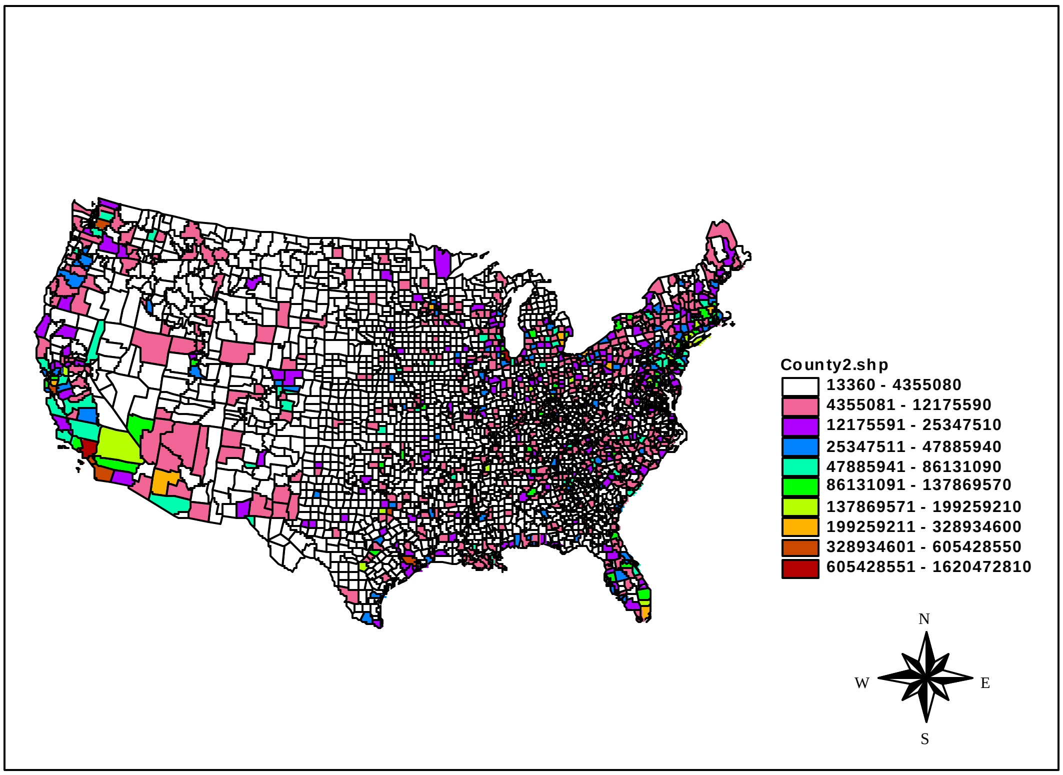
Source: USA Counties 1998 CD-ROM

Appendix Figure A-10: U.S. Population Density per Square Mile in 1,000 (Year 1992)



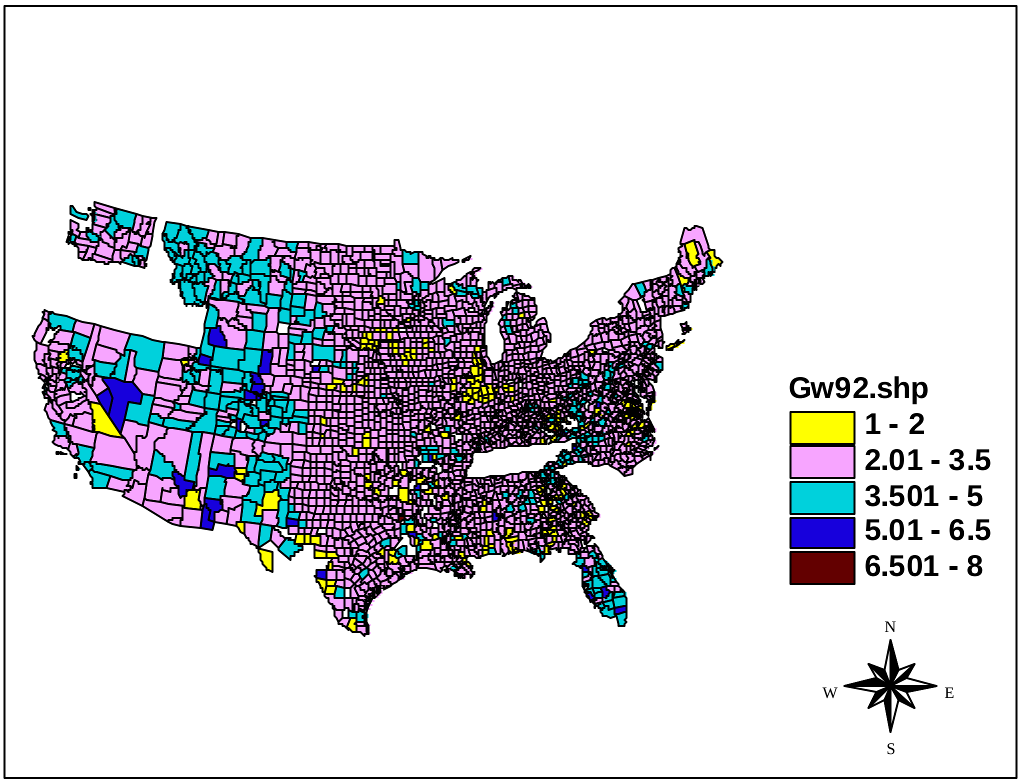
Source: USA Counties 1998 CD-ROM

Appendix Figure A-11: U.S. County-Level Earnings in All Industries In Dollars (Year 1992)



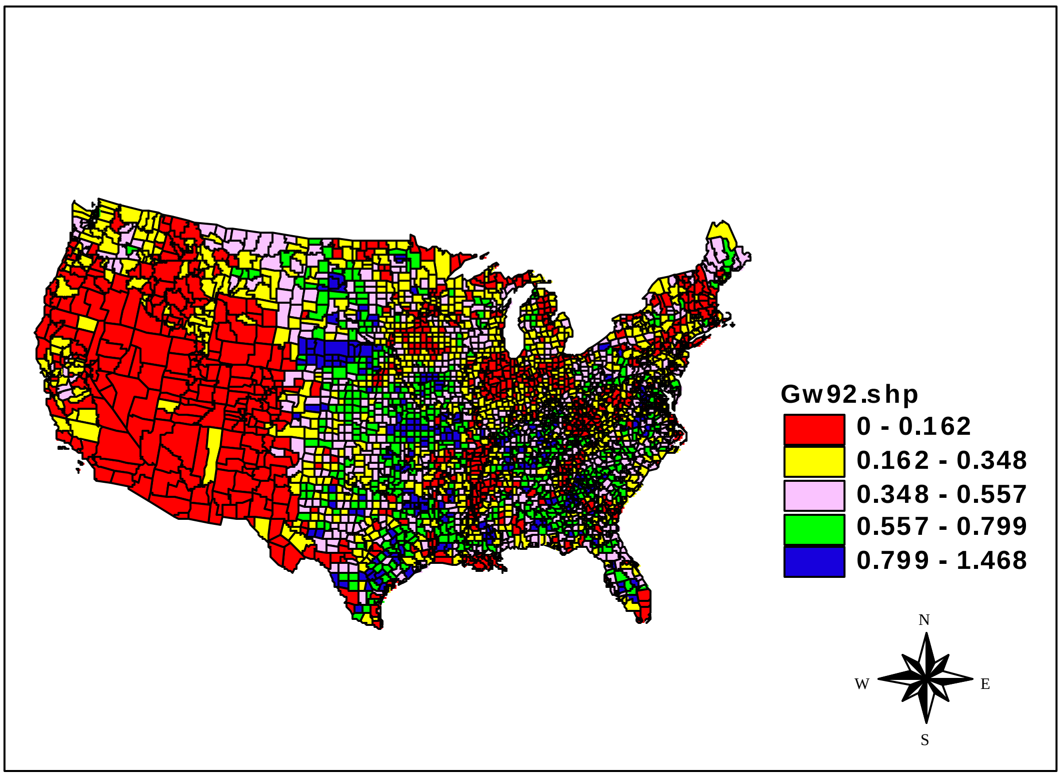
Source: USA Counties 1998 CD-ROM

Appendix Figure A-12: U.S. Cropland Capability Class
(Year 1992)



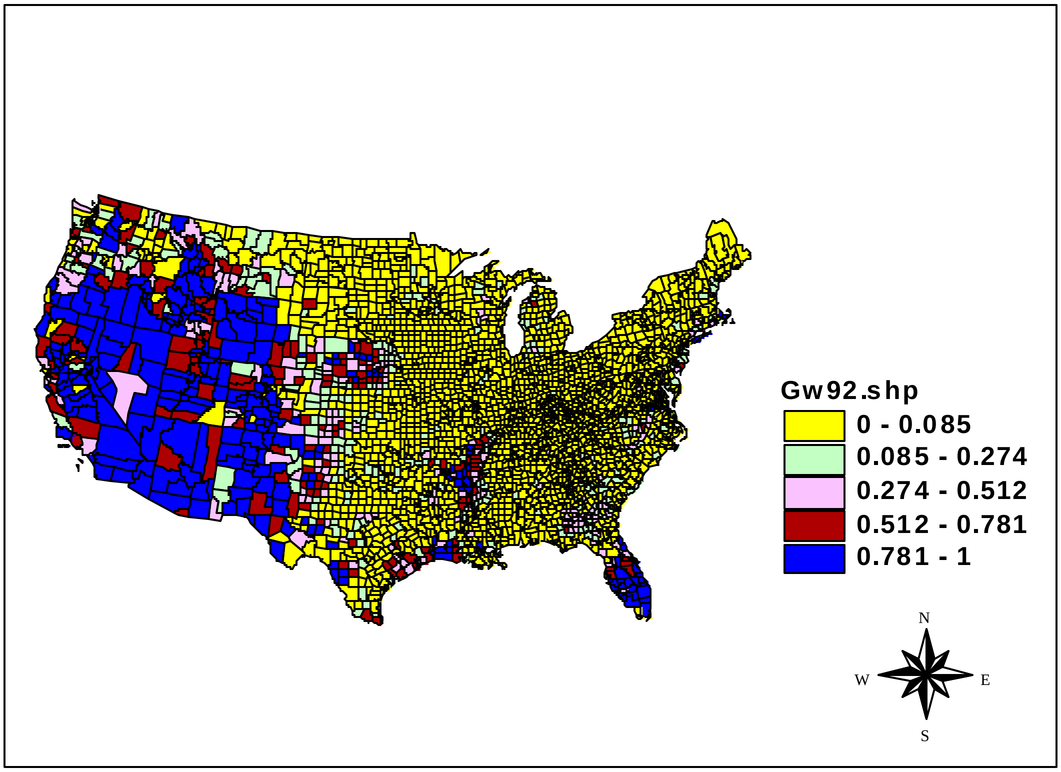
Source: 1992 National Resource Inventory (NRI)

Appendix Figure A-13: U.S. Potential Conversion to Cropland (Year 1992)



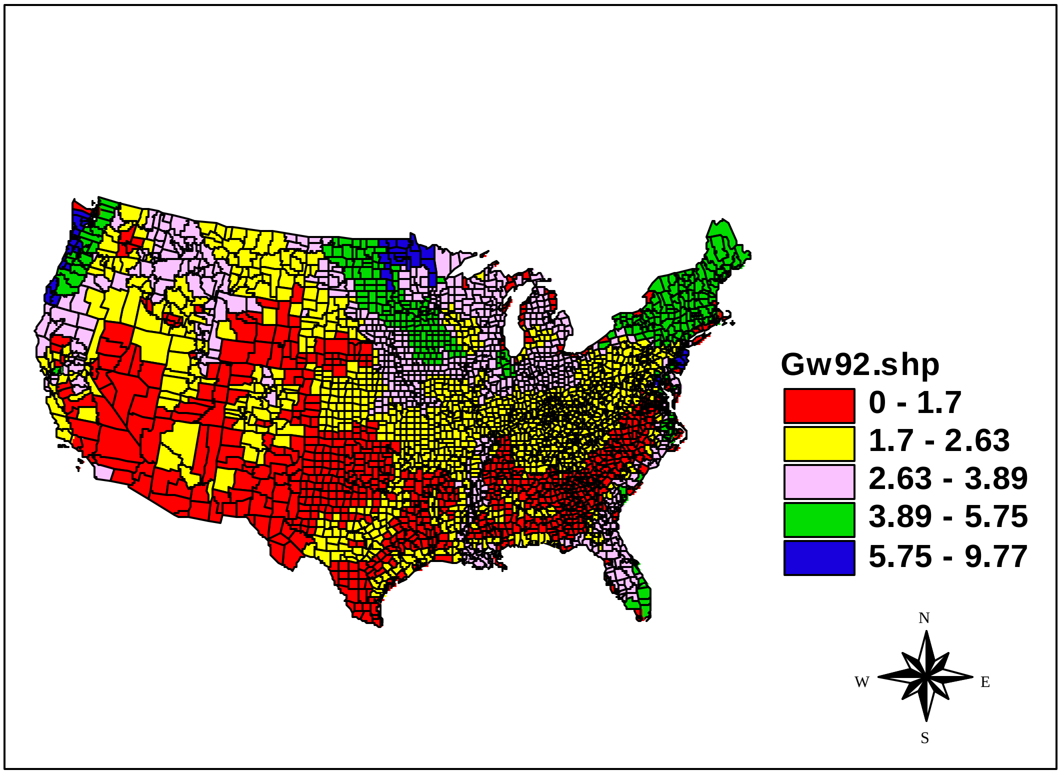
Source: 1992 National Resource Inventory (NRI)

Appendix Figure A-14: U.S. Proportion of Cropland that has irrigation Source (Year 1992)



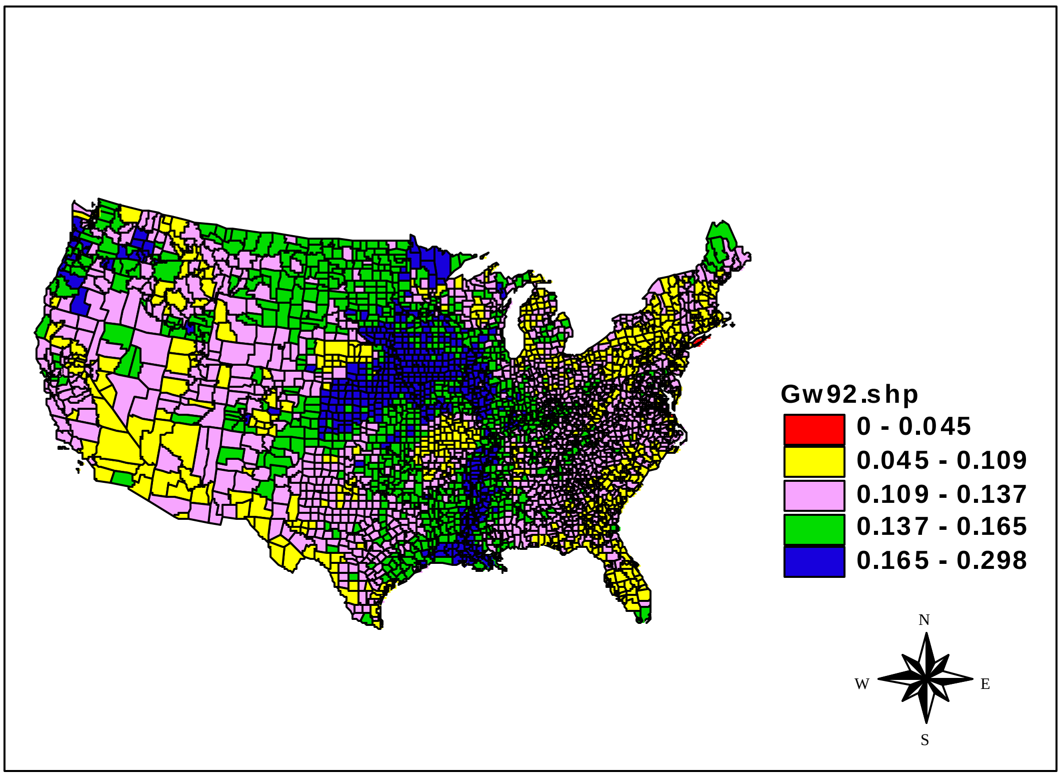
Source: 1992 National Resource Inventory (NRI)

Appendix Figure A-15: U.S. Organic Matter



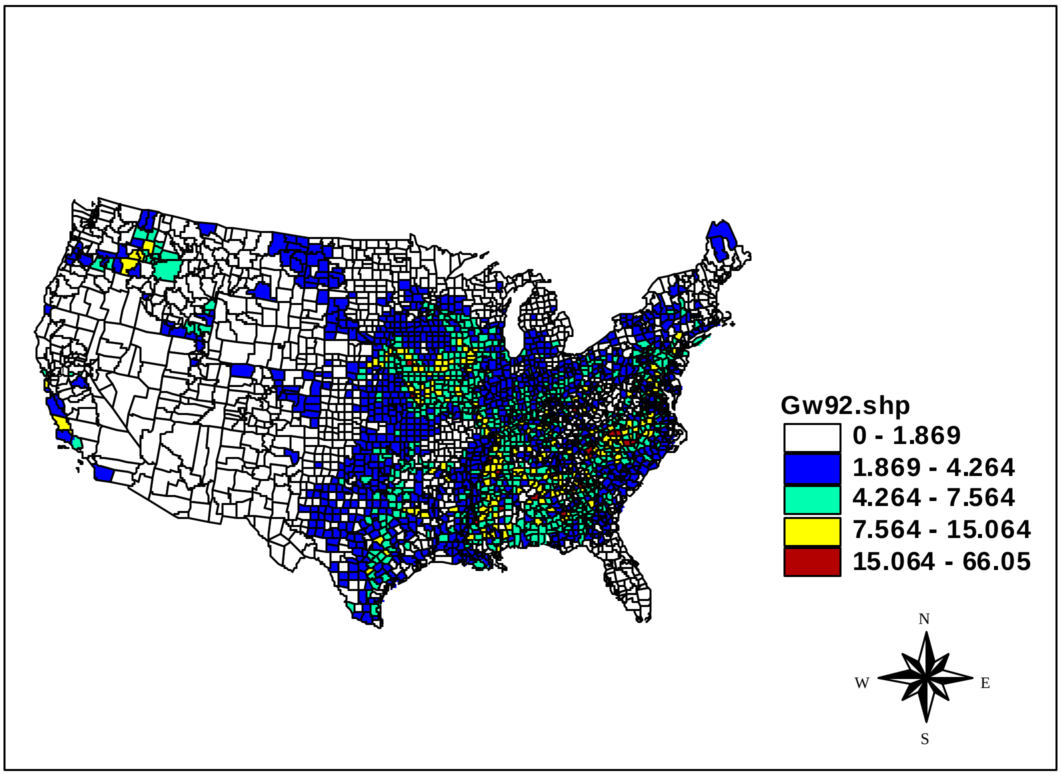
Source: 1992 National Resource Inventory (NRI)

Appendix Figure A-16: U.S. Available Water Capacity



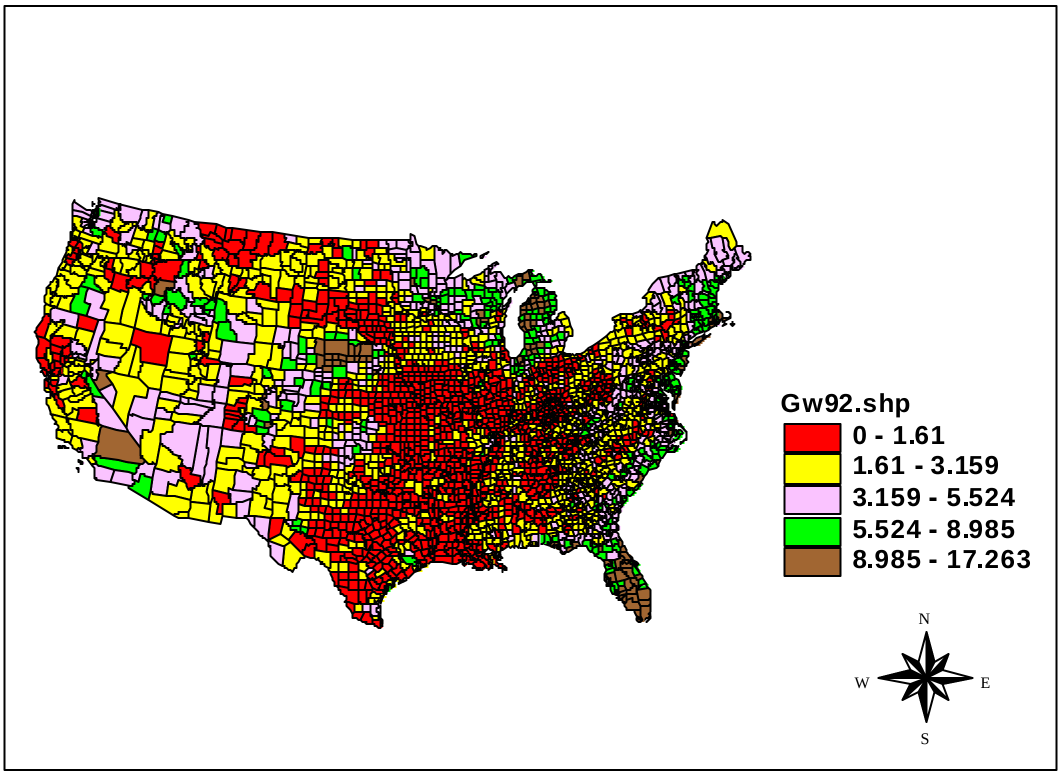
Source: 1992 National Resource Inventory (NRI)

Appendix Figure A-17: U.S. Universal Soil Loss Equation (USLE) for Cropland (Year 1992)



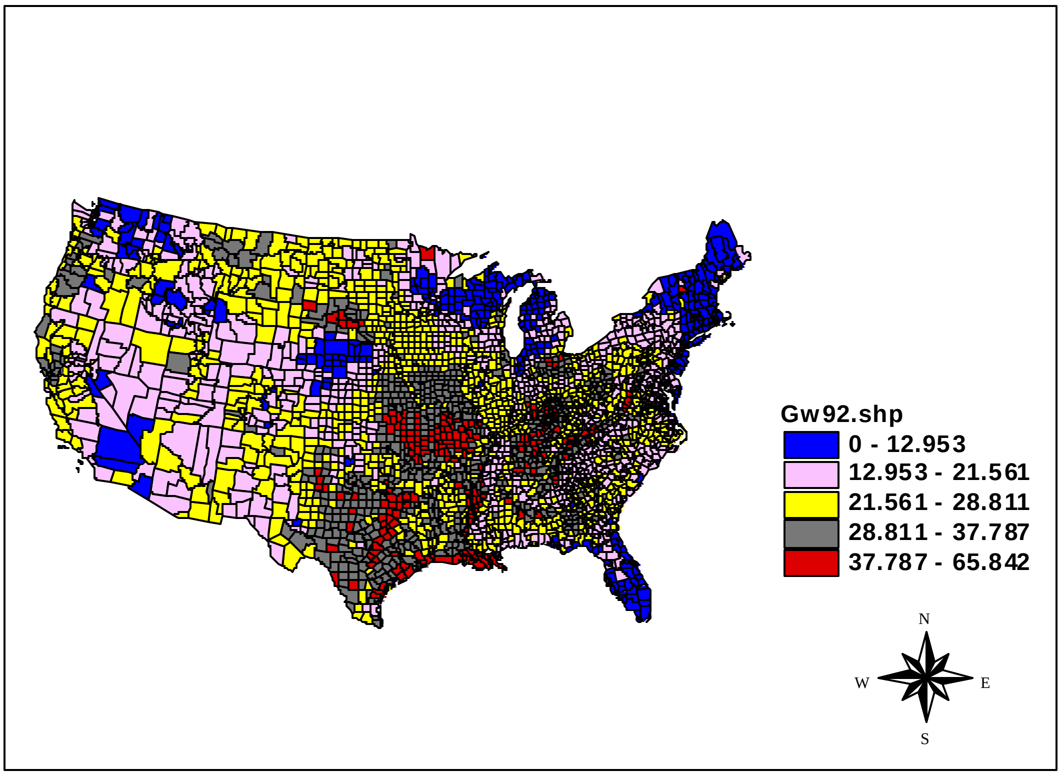
Source: 1992 National Resource Inventory (NRI)

Appendix Figure A-18: U.S. Permeability



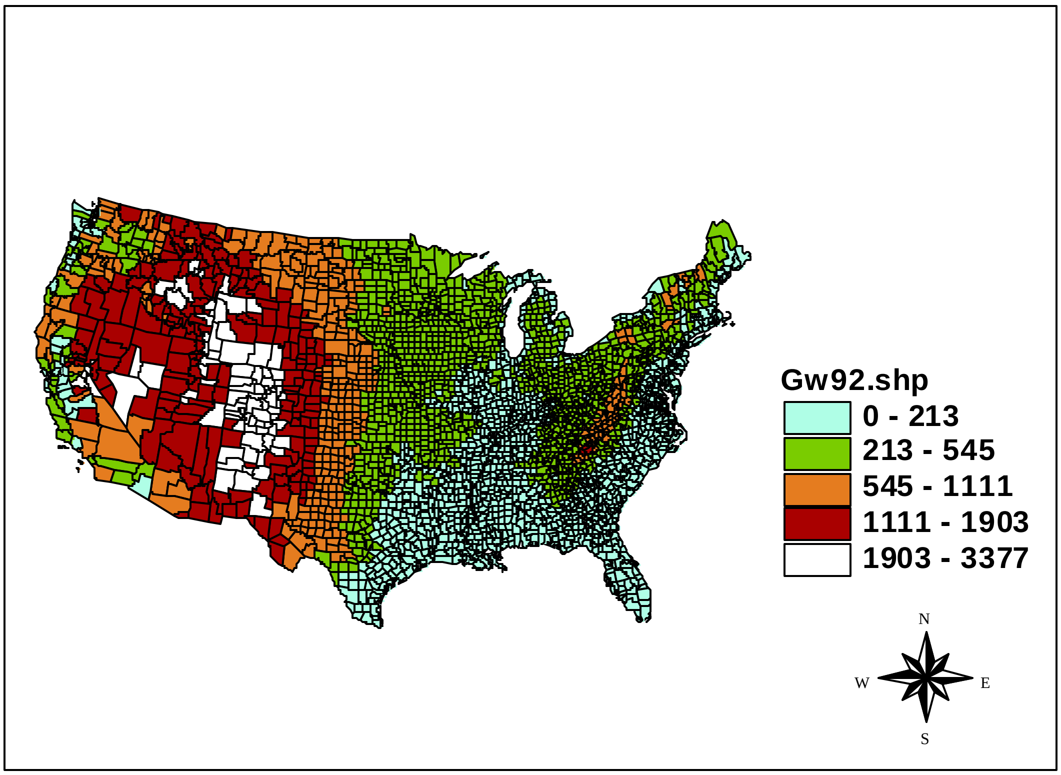
Source: 1992 National Resource Inventory (NRI)

Appendix Figure A-19: U.S. Clay



Source: 1992 National Resource Inventory (NRI)

Appendix Figure A-20: U.S. Elevation (m)



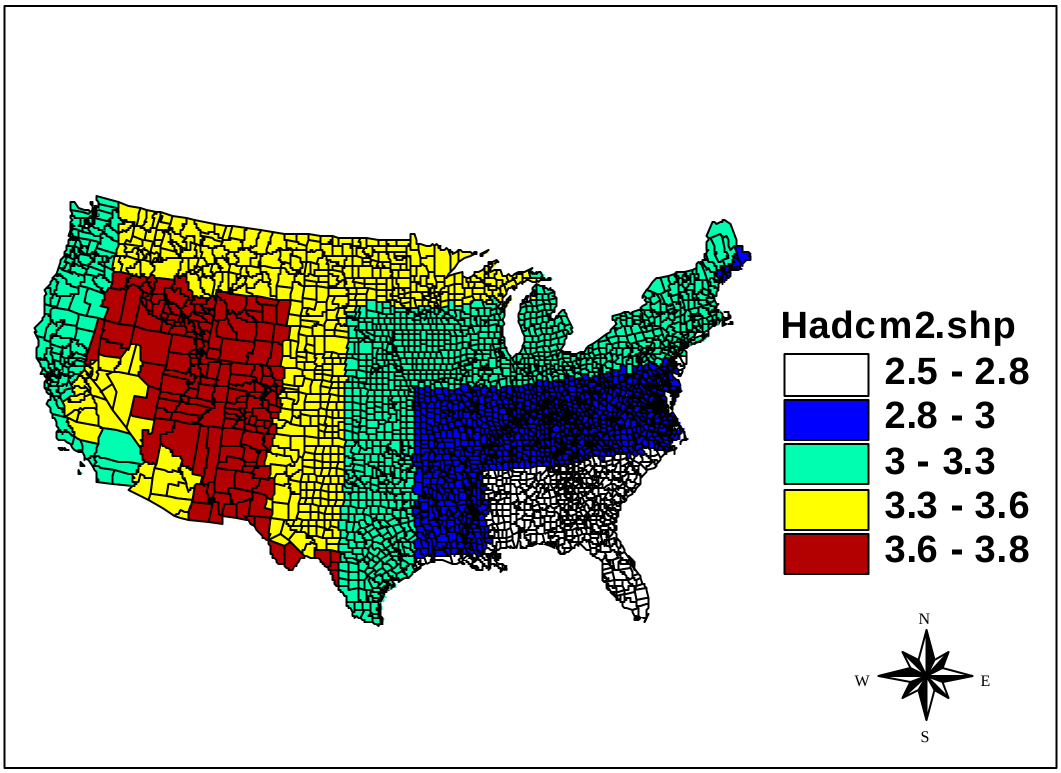
Source: VEMAP

APPENDIX FIGURE B

Appendix Figure B-1: HadCM2-based
Projected Annual Average Temperature Change, in °C

Relative to Baseline Period 1961-1990

(2061-2090, °C, High Climate Sensitivity)

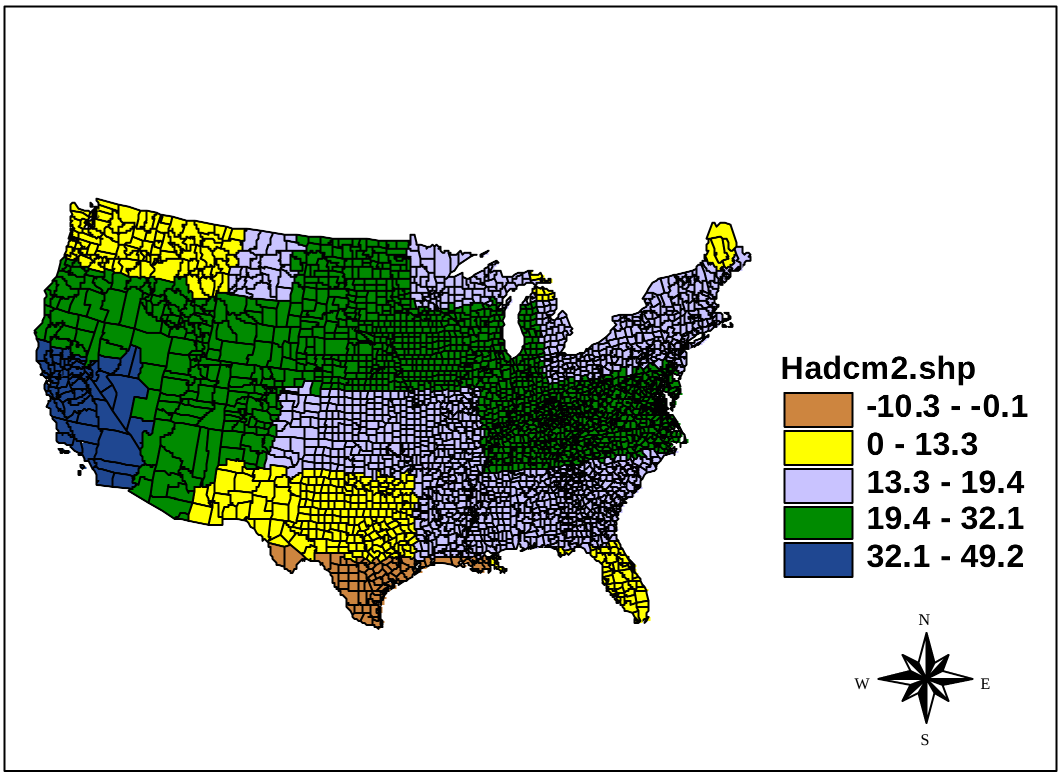


Source: MAGICC/SCENGEN (Version 2.4)

Appendix Figure B-2: HadCM2-based
Projected Annual Average Precipitation (% change)

Relative to Baseline Period 1961-1990

(2061-2090, High Climate Sensitivity)

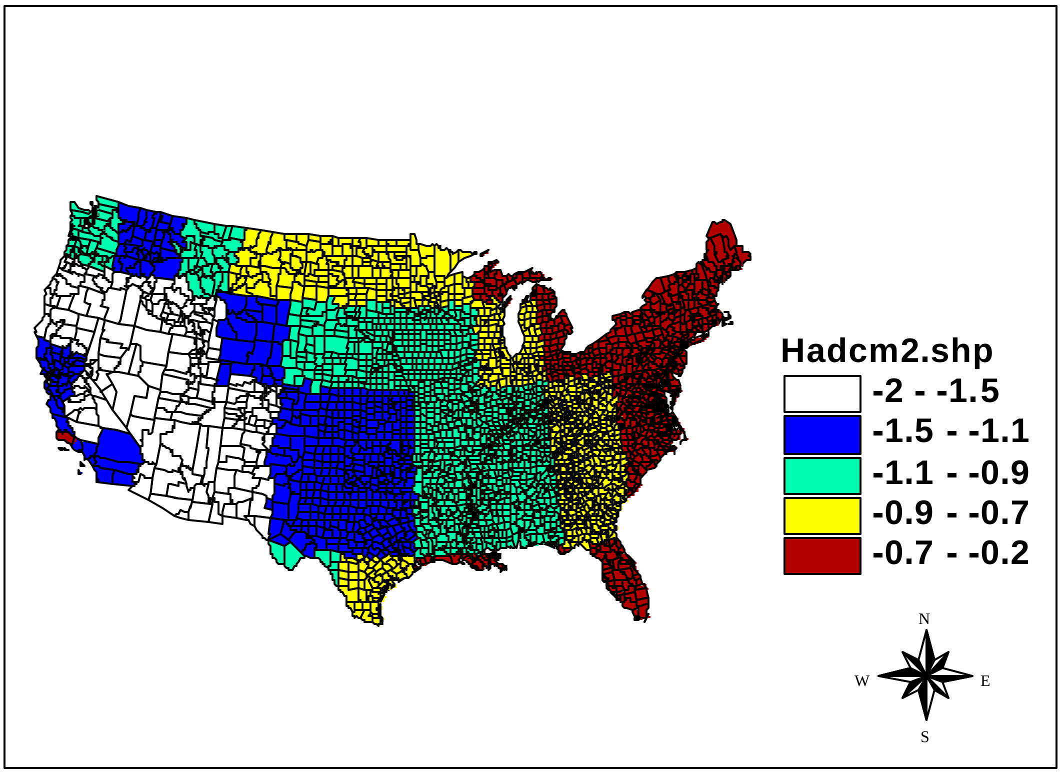


Source: MAGICC/SCENGEN (Version 2.4)

Appendix Figure B-3: HadCM2-based
Change in the Annual Daily Temperature Range, in °C

Relative to Baseline Period 1961-1990

(2061-2090, °C, High Climate Sensitivity)

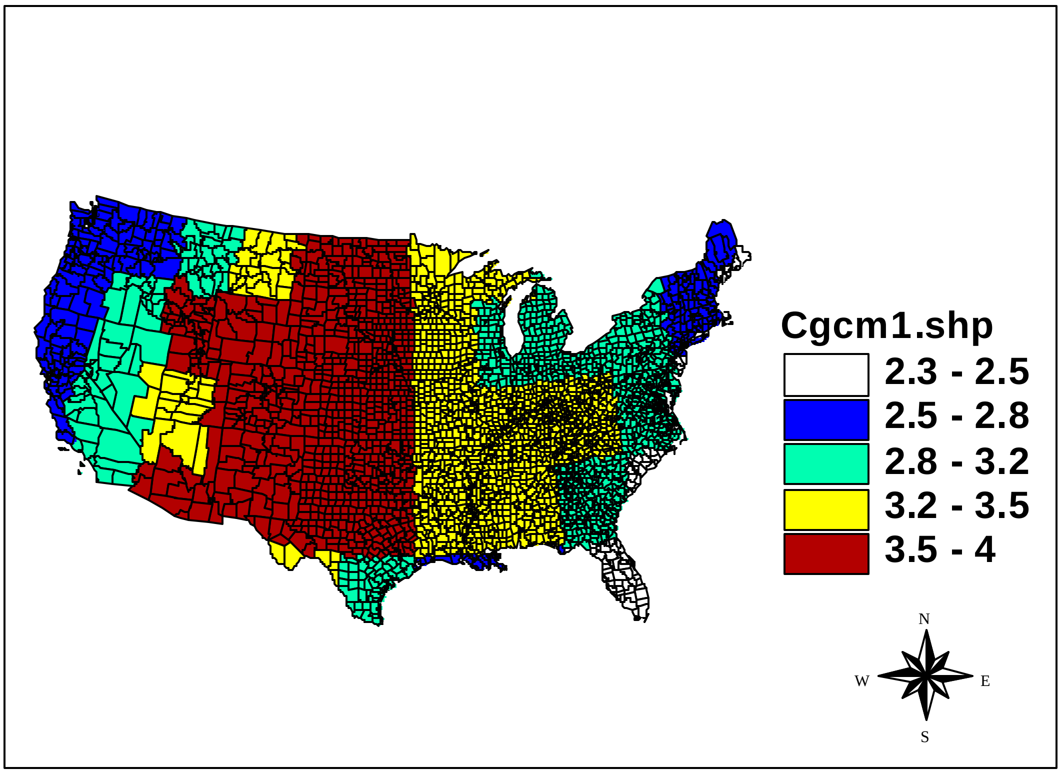


Source: MAGICC/SCENGEN (Version 2.4)

Appendix Figure B-4: CGCM1-TR-based Projected Annual Average Temperature Change, in °C

Relative to Baseline Period 1961-1990

(2061-2090, °C, High Climate Sensitivity)

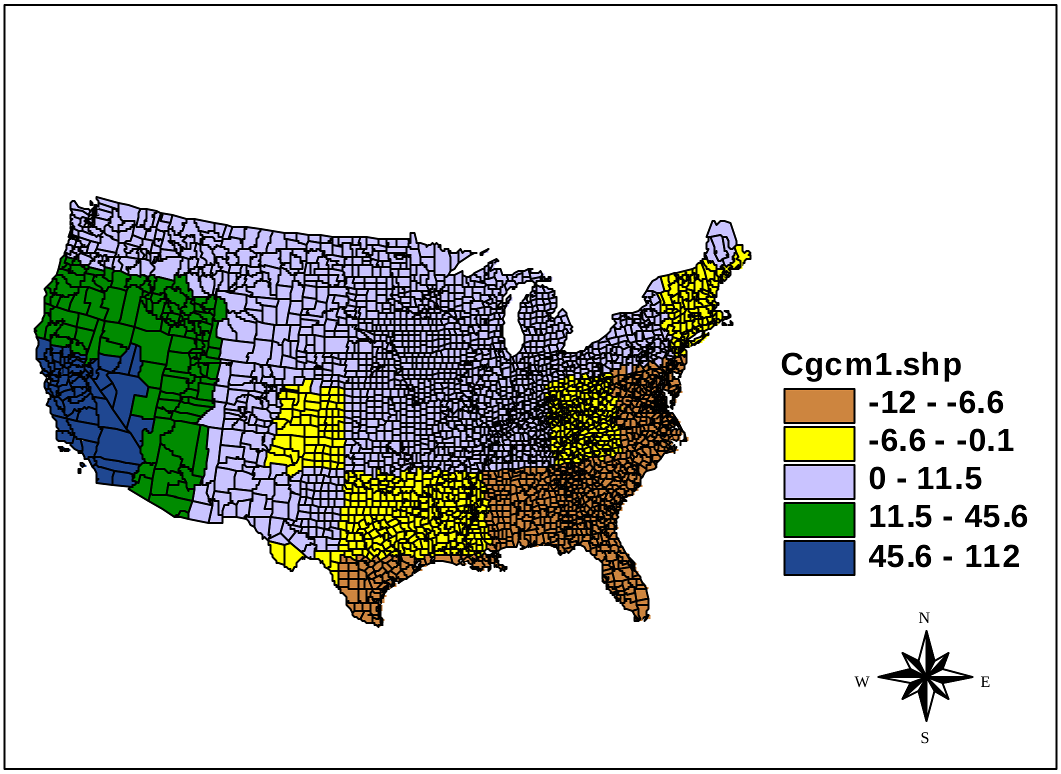


Source: MAGICC/SCENGEN (Version 2.4)

Appendix Figure B-5: CGCM1-TR-based
Projected Annual Average Precipitation (% change)

Relative to Baseline Period 1961-1990

(2061-2090, High Climate Sensitivity)

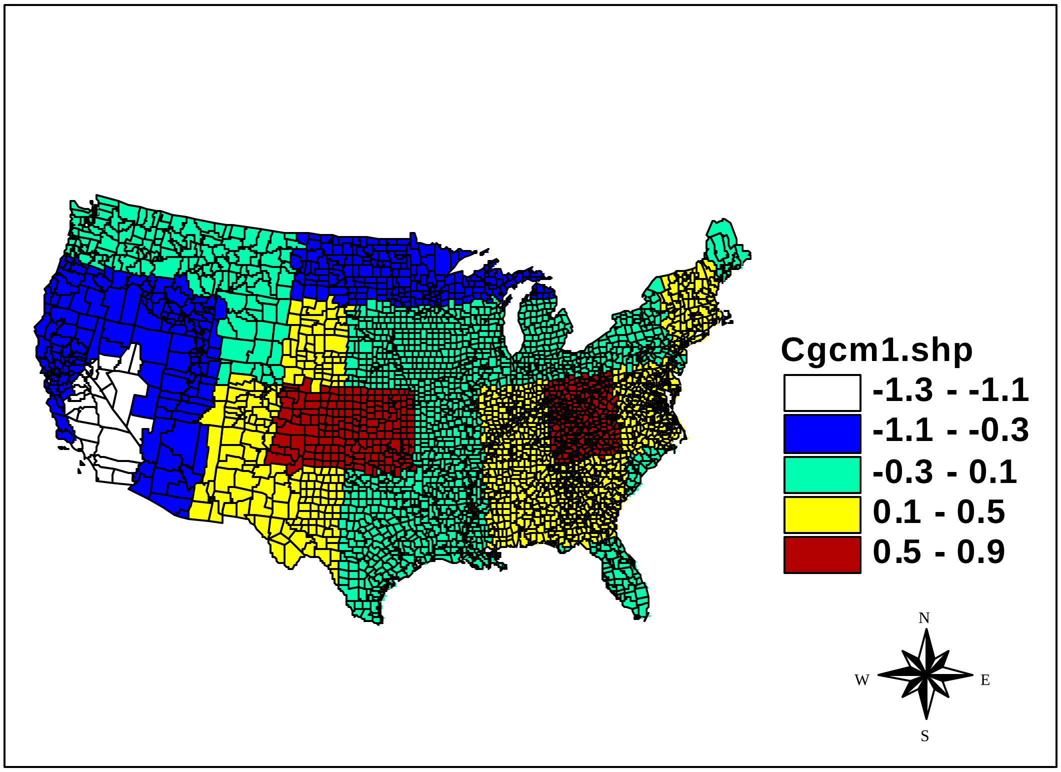


Source: MAGICC/SCENGEN (Version 2.4)

Appendix Figure B-6: CGCM1-TR-based Change in the Annual Daily Temperature Range, in °C

Relative to Baseline Period 1961-1990

(2061-2090, °C, High Climate Sensitivity)

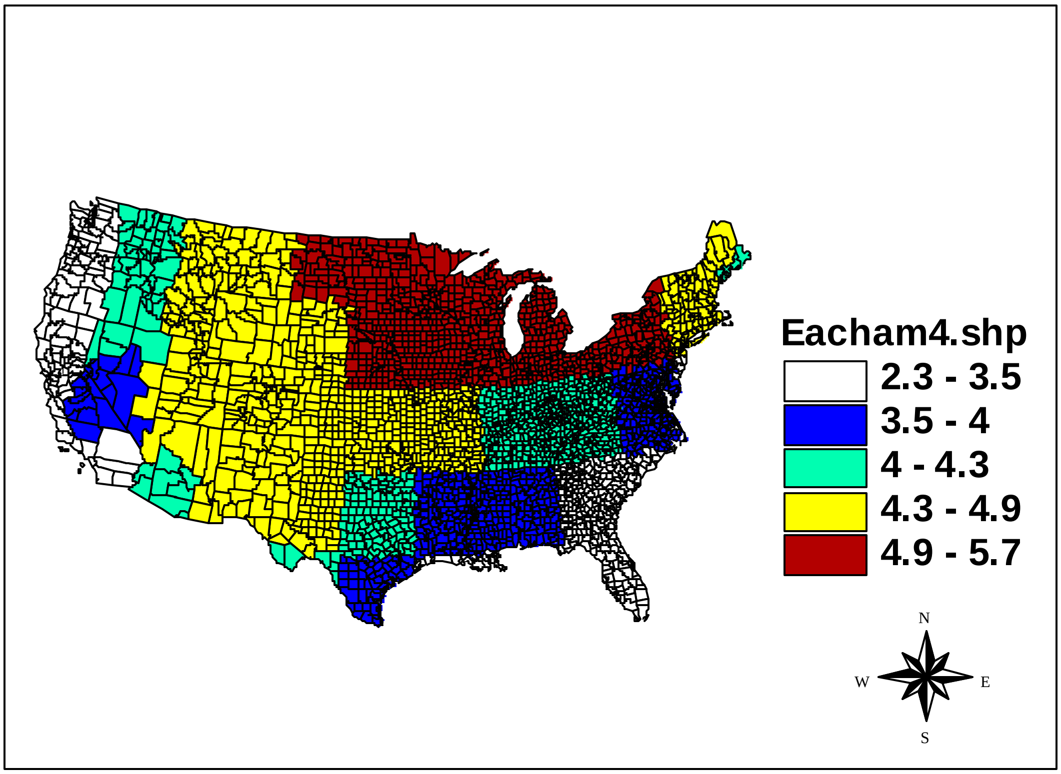


Source: MAGICC/SCENGEN (Version 2.4)

Appendix Figure B-7: EACHAM4-based
Projected Annual Average Temperature Change, in °C

Relative to Baseline Period 1961-1990

(2061-2090, °C, High Climate Sensitivity)

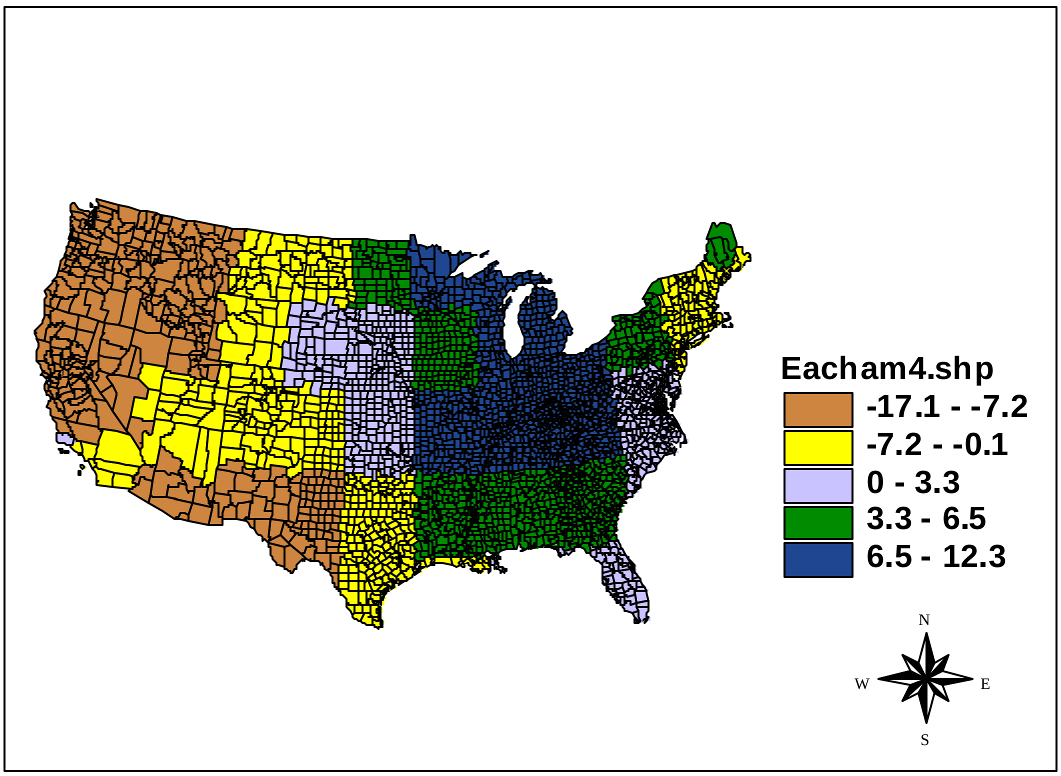


Source: MAGICC/SCENGEN (Version 2.4)

Appendix Figure B-8: EACHAM4-based Projected Annual Average Precipitation (% change)

Relative to Baseline Period 1961-1990

(2061-2090, High Climate Sensitivity)

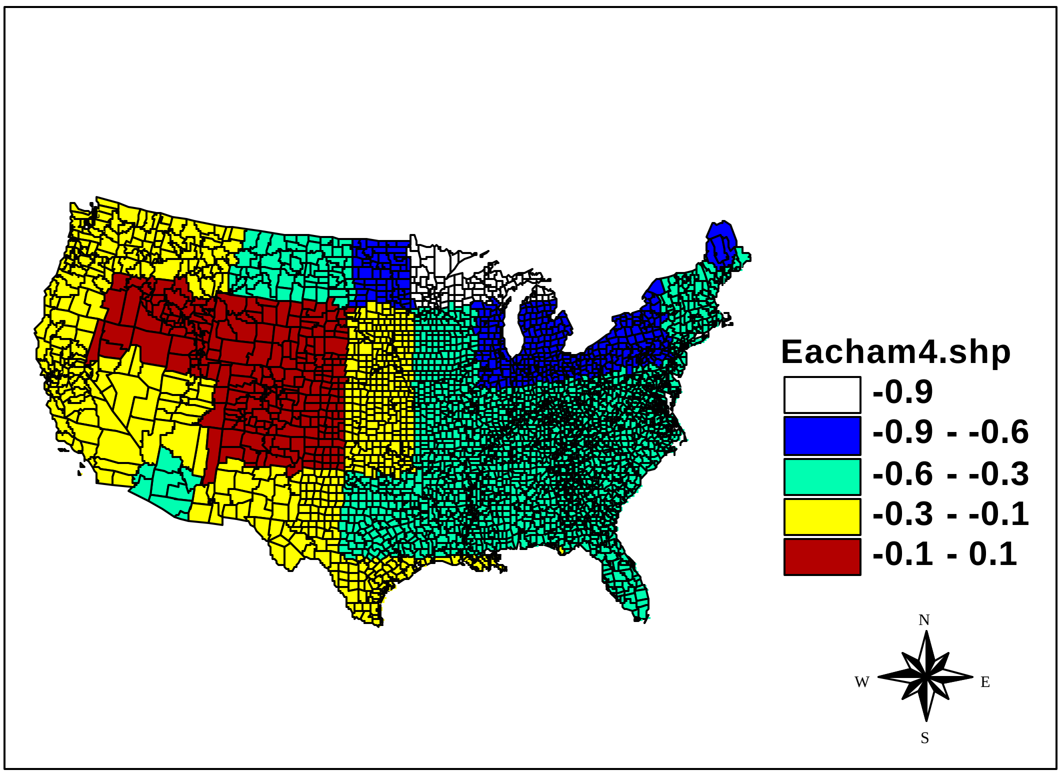


Source: MAGICC/SCENGEN (Version 2.4)

Appendix Figure B-9: EACHAM4-based Change in the Annual Daily Temperature Range, in °C

Relative to Baseline Period 1961-1990

(2061-2090, °C, High Climate Sensitivity)



Source: MAGICC/SCENGEN (Version 2.4)

APPENDIX TABLE

Appendix Table 1: Change in Present Value of Farmland per Acre in 1996 Million Dollars: The Appalachian Region (WV, VA, KY, TN, NC)

GCM	Climate Sensitivity	2001-2030	2031-2060	2061-2090
CGCM1-TR	*1.5˚C*	-35	-109	-226
	4.5˚C	-96	-196	-374
EACHAM4	*1.5˚C*	83	261	311
	4.5˚C	231	387	678
HadCM2	*1.5˚C*	135	259	370
	4.5˚C	200	519	856
Average		86	187	269

Appendix Table 2: Change in Present Value of Farmland per Acre in 1996 Million Dollars: The Corn Belt (IA, IL, MO, IN, OH)

GCM	Climate Sensitivity	2001-2030	2031-2060	2061-2090
CGCM1-TR	*1.5˚C*	-38	-257	-352
	4.5˚C	-140	-316	-637
EACHAM4	*1.5˚C*	603	1,378	2,147
	4.5˚C	1,275	2,561	4,239
HadCM2	*1.5˚C*	660	1,266	2,024
	4.5˚C	1,108	2,506	4,024
Average		578	1,190	1,908

Appendix Table 3: Change in Present Value of Farmland per Acre in 1996 Million Dollars: The Delta States (AR, LA, MS)

GCM	Climate Sensitivity	2001-2030	2031-2060	2061-2090
CGCM1-TR	*1.5˚C*	-91	-130	-202
	4.5˚C	-128	-307	-476
EACHAM4	*1.5˚C*	89	207	357
	4.5˚C	221	397	612
HadCM2	*1.5˚C*	40	92	109
	4.5˚C	50	142	190
Average		30	67	98

Appendix Table 4: Change in Present Value of Farmland per Acre in 1996 Million Dollars: The Lake States (MN, WI, MI)

GCM	Climate Sensitivity	2001-2030	2031-2060	2061-2090
CGCM1-TR	*1.5˚C*	161	283	494
	4.5˚C	291	691	1,045
EACHAM4	*1.5˚C*	293	554	876
	4.5˚C	500	1,121	1,791
HadCM2	*1.5˚C*	241	404	654
	4.5˚C	363	816	1,282
Average		308	645	1,024

Appendix Table 5: Change in Present Value of Farmland per Acre in 1996 Million Dollars: The Mountain Region (MT, ID, WY, NV, UT, CO, AZ, NM)

GCM	Climate Sensitivity	2001-2030	2031-2060	2061-2090
CGCM1-TR	*1.5°C*	77	175	244
	4.5°C	138	313	507
EACHAM4	*1.5°C*	88	152	272
	4.5°C	136	352	552
HadCM2	*1.5°C*	105	197	310
	4.5°C	178	385	631
Average		120	262	419

Appendix Table 6: Change in Present Value of Farmland per Acre in 1996 Million Dollars: The Northern Plains (ND, SD, NE, KS)

GCM	Climate Sensitivity	2001-2030	2031-2060	2061-2090
CGCM1-TR	*1.5°C*	95	270	318
	4.5°C	213	477	769
EACHAM4	*1.5°C*	342	556	892
	4.5°C	529	1,207	1,909
HadCM2	*1.5°C*	287	595	908
	4.5°C	482	1,127	1,831
Average		325	705	1,105

Appendix Table 7: Change in Present Value of Farmland per Acre in 1996 Million Dollars: The Northeast Region (ME, NH, VT, RI, CT, NJ, DE, MA, PA, MD, NY)

GCM	Climate Sensitivity	2001-2030	2031-2060	2061-2090
CGCM1-TR	*1.5˚C*	56	184	204
	4.5˚C	138	294	461
EACHAM4	*1.5˚C*	176	331	470
	4.5˚C	279	622	1,015
HadCM2	*1.5˚C*	12	104	146
	4.5˚C	41	233	322
Average		117	295	436

Appendix Table 8: Change in Present Value of Farmland per Acre in 1996 Million Dollars: The Pacific Region (WA, OR, CA)

GCM	Climate Sensitivity	2001-2030	2031-2060	2061-2090
CGCM1-TR	*1.5˚C*	95	114	181
	4.5˚C	92	304	436
EACHAM4	*1.5˚C*	153	247	383
	4.5˚C	220	495	742
HadCM2	*1.5˚C*	203	410	624
	4.5˚C	342	786	1,293
Average		184	393	610

Appendix Table 9: Change in Present Value of Farmland per Acre in 1996 Million Dollars: The Southern Plains (TX, OK)

GCM	Climate Sensitivity	2001-2030	2031-2060	2061-2090
CGCM1-TR	*1.5°C*	-120	-318	-502
	4.5°C	-274	-652	-1,024
EACHAM4	*1.5°C*	140	338	514
	4.5°C	355	666	1,085
HadCM2	*1.5°C*	-51	-68	-92
	4.5°C	-79	-130	-275
Average		-5	-27	-49

Appendix Table 10: Change in Present Value of Farmland per Acre in 1996 Million Dollars: The Southeast Region (AL, GA, SC, FL)

GCM	Climate Sensitivity	2001-2030	2031-2060	2061-2090
CGCM1-TR	*1.5°C*	31	69	111
	4.5°C	50	144	239
EACHAM4	*1.5°C*	81	162	246
	4.5°C	141	306	482
HadCM2	*1.5°C*	18	58	14
	4.5°C	21	28	90
Average		57	128	197

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Vita

Young Sin Yoo was born in Seoul, Korea, on August 5, 1965 to Sunghwan Yoo and Chokang Lee. He is a graduate of Kyunggi High School in Seoul, Korea. In 1989, Young earned a Bachelor of Arts in Philosophy at Yonsei University in Seoul, Korea. In 1994, he graduated Summa Cum Laude at Washington State University in Pullman with a Bachelor's degree in economics. Young earned a Masters degree in economics at the University of Texas at Austin in 1999 with a specialization in public finance. He continued at the University of Texas, pursuing a Ph.D. in economics. His main research areas were: environmental and natural resource economics, public finance, and economics of regulation and market failure. From 1998-99, he served as the president of Korean Graduate Student Association at the University of Texas at Austin. Since May 1999, he has also worked as an economic consultant for Magee & Magee in Austin, Texas.

Permanent address: 9283 Dexter-Chelsea Rd., Dexter, MI 48130

This dissertation was typed by Young Sin Yoo